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CrisisBench: Benchmarking Crisis-related Social Media Datasets for Humanitarian Information Processing

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Abstract

Time-critical analysis of social media streams is important for humanitarian organizations for planing rapid response during disasters. The *crisis informatics* research community has developed several techniques and systems for processing and classifying big crisis-related data posted on social media. However, due to the dispersed nature of the datasets used in the literature (e.g., for training models), it is not possible to compare the results and measure the progress made towards building better models for crisis informatics tasks. In this work, we attempt to bridge this gap by combining various existing crisis-related datasets. We consolidate eight human-annotated datasets and provide 166.1k and 141.5k tweets for *informativeness* and *humanitarian* classification tasks, respectively. We believe that the consolidated dataset will help train more sophisticated models. Moreover, we provide benchmarks for both binary and multiclass classification tasks using several deep learning architecrures including, CNN, fastText, and transformers. We make the dataset and scripts available at `https://crisisnlp.qcri.org/crisis_datasets_benchmarks.html`.

1 Introduction

At the onset of a disaster event, information pertinent to situational awareness such as reports of injured, trapped, or deceased people, urgent needs of victims, and infrastructure damage reports are most needed by formal humanitarian organizations to plan and launch relief operations. Acquiring such information in real-time is ideal to understand the situation as it unfolds. However, it is challenging as traditional methods such as field assessments and surveys are time-consuming. Microblogging platforms such as Twitter have been widely used to disseminate situational and actionable information by the affected population. Although social media sources are useful in this time-critical setting, it is, however, challenging to parse and extract actionable information from big crisis data available on social media (Castillo 2016).

The past couple of years have witnessed a surge in the research works that focus on analyzing the usefulness of social media data and developing computational models to extract actionable information. Among others, proposed computational techniques include, information classification, information extraction, and summarization (Imran et al. 2015). Most of these studies use one of the publicly available datasets (Olteanu et al. 2014; Imran, Mitra, and Castillo 2016; Alam et al. 2018, 2020) and either propose a new model or report higher performance of an existing model. Typical classification tasks in the community include (i) *informativeness* (i.e., informative vs. not-informative messages), (ii) *humanitarian information types* (e.g., affected individual reports, infrastructure damage reports), and (iii) *event types* (e.g., flood, earthquake, fire).

Despite the recent focus of the *crisis informatics*[1] research community to develop novel and more robust computational algorithms and techniques to process social media data, we observe several limitations in the current literature. *First*, few efforts have been invested to develop standard datasets (specifically, train/dev/test splits) and benchmarks for the community to compare their results, models, and techniques. *Secondly*, most of the published datasets are noisy, e.g., CrisisLex (Olteanu et al. 2014) contains duplicate and near-duplicate content, which produces misleading classification performance. Moreover, some datasets (e.g., CrisisLex) consist of tweets from several languages without any explicit language tag, to separate the data of a particular language of interest.

To address such limitations, in this paper, we aim to develop a standard social media dataset for disaster response that facilitates comparison between different modeling approaches and encourages the community to streamline their efforts towards a common goal. We consolidate eight publicly available datasets (see Section 3). The resulting dataset is larger in size, has better class distribution compared to the individual datasets, and enables building of robust models that performs better for various tasks (i.e., informativeness and humanitarian) and datasets.

The consolidation of datasets from different sources involves various standardization challenges. One of the challenges is the inconsistent class labels across various data sources. We map the class labels using their semantic meaning—a step performed by domain experts manually.

[1] `https://en.wikipedia.org/wiki/Disaster_informatics`

Another challenge is to tackle the duplicate content that is present within or across datasets. There are three types of duplicates: *(i)* tweet-id based duplicates (i.e., same tweet appears in different datasets), *(ii)* content-based duplicates (i.e., tweets with different ids have same content), which usually happens when users copy-paste tweets, and *(iii)* near-duplicate content (i.e., tweets with similar content), which happens due to retweets or partial copy of tweets from other users. We use cosine similarity between tweets to filter out various types of duplicates. In summary, the contributions of this study are as follows:

- We consolidate eight publicly available disaster-related datasets by manually mapping semantically similar class labels, which leads to a larger dataset.
- We carefully cleaned various forms of duplicates, and assigned a language tag to each tweet.
- We provide benchmark results on English tweets set using state-of-the-art machine learning algorithms such as Convolutional Neural Networks (CNN), fastText (Joulin et al. 2017) and pre-trained transformer models (Devlin et al. 2019) for two classifications tasks, i.e., *Informativeness* (binary) and *Humanitarian type* (multi-class) classification.[2] The benchmarking encourages the community towards a comparable and reproducible research.
- For the research community, we aim to release the dataset in multiple forms as, *(i)* a consolidated class label mapped version, *(ii)* exact- and near-duplicate filtered version obtained from previous versions, *(iii)* a subset of the filtered data used for the classification experiments in this study.

The rest of the paper is organized as follows. Section 2 provides an overview of the existing work. Section 3 describes our data curation and consolidation procedures, and Section 4 describes the experiments. Section 5 presents and discusses the results. Finally, Section 6 concludes the paper.

2 Related Work

2.1 Dataset Consolidation

In *crisis informatics* research on social media, there has been an effort to develop datasets for the research community. An extensive literature review can be found in (Imran et al. 2015). Although there are several publicly available datasets that are used by the researchers, their results are not exactly comparable due to the differences in class labels and train/dev/test splits. In addition, the issue of exact- and near-duplicate content in existing datasets can lead to misleading performance as mentioned earlier. This problem become more visible while consolidating existing datasets. Alam, Muhammad, and Ferda (2019); Kersten et al. (2019) and Wiegmann et al. (2020) have previously worked in the direction to consolidate social media disaster response data. A major limitation of the work by Alam, Muhammad, and Ferda (2019) is that the issue of duplicate and near-duplicate content have not been addressed when combining the different datasets. This issue resulted in an overlap between train and test sets. In terms of label mapping the work of Alam, Muhammad, and Ferda (2019) is similar to the current study. Kersten et al. (2019) focused only on informativeness[3] classification and combined five different datasets. This study has also not focused on exact- and near-duplicate content, which exist in different datasets. The study in Wiegmann et al. (2020) also compiled existing resources for *disaster event types* (e.g., Flood, Fire) classification, which consists of a total of 123,166 tweets from 46 disasters with 9 disaster types. This is different from our work as we address *informativeness* and *humanitarian* classification tasks. Addressing *disaster event types* classification is beyond the scope of our current study.

A fair comparison of the classification experiment is also difficult with previous studies as their train/dev/test splits are not public, except the dataset by Wiegmann et al. (2020). We address such limitations in this study, i.e., we consolidate the datasets, eliminate duplicates, and release standard dataset splits with benchmark results.

In terms of defining class labels (i.e., tagsets) for crisis informatics, most of the earlier efforts are discussed in (Imran et al. 2015; Temnikova, Castillo, and Vieweg 2015; Stowe et al. 2018; Wiegmann et al. 2020). Various recent studies (Olteanu et al. 2014; Imran, Mitra, and Castillo 2016; Alam et al. 2018; Stowe et al. 2018) use similar definitions for class labels. Unlike them, (Strassel, Bies, and Tracey 2017) defines more fine-grained categories based on need types (e.g., evacuation, food supply) and issue type (e.g., civil unrest). In this study, we use the class labels that are important for humanitarian aid for disaster response tasks, which are common across the publicly available resources. Some of the real-time applications that are currently using such labels include AIDR (Imran et al. 2014), CREES (Burel and Alani 2018), and TweetTracker (Kumar et al. 2011).

2.2 Classification Algorithms

Despite the fact that a majority of studies in *crisis informatics* literature employ traditional machine learning algorithms, several recent works explore deep learning algorithms in disaster-related tweet classification tasks. The study of (Nguyen et al. 2017) and (Neppalli, Caragea, and Caragea 2018) performed comparative experiments between different classical and deep learning algorithms including Support Vector Machines, Logistic Regression, Random Forests, Recurrent Neural Networks, and Convolutional Neural Networks (CNN). Their experimental results suggest that CNN outperforms other algorithms. Though in another study, (Burel and Alani 2018) reports that SVM and CNN can provide very competitive results in some cases. CNNs have also been explored in event type-specific filtering model (Kersten et al. 2019) and few-shot learning (Kruspe, Kersten, and Klan 2019). Very recently different types of embedding representations have been proposed in literature such as Embeddings from Language Models (ELMo) (Peters et al. 2018), Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019), and XLNet (Yang et al. 2019) for different NLP tasks. The

[2] We only focused on two tasks for this study and we aim to address *event types* task in a future study.

[3] Authors used *related* vs. *not-related* in their study.

study by (Jain, Ross, and Schoen-Phelan 2019) and (Wiegmann et al. 2020) investigates these embedding representations for disaster tweet classification tasks.

3 Data Curation

3.1 Data Consolidation

We consolidate eight datasets that were labeled for different disaster response classification tasks and whose labels can be mapped consistently for two tasks: *informativeness* and *humanitarian information type* classification. In doing so, we deal with two major challenges: *(i)* discrepancies in the class labels used across different datasets, and *(ii)* exact- and near-duplicate content that exists within as well as across different datasets. Below we provide a brief overview of the datasets we used for consolidation.

1. **CrisisLex** is one of the largest publicly-available datasets, which consists of two subsets, i.e., CrisisLexT26 and CrisisLexT6 (Olteanu et al. 2014). CrisisLexT26 comprises data from 26 different crisis events that took place in 2012 and 2013 with annotations for informative vs. not-informative as well as humanitarian categories (six classes) classification tasks among others. CrisisLexT6, on the other hand, contains data from six crisis events that occurred between October 2012 and July 2013 with annotations for *related* vs. *not-related* binary classification task.
2. **CrisisNLP** is another large-scale dataset collected during 19 different disaster events that happened between 2013 and 2015, and annotated according to different schemes including classes from humanitarian disaster response and some classes related to health emergencies (Imran, Mitra, and Castillo 2016).
3. **SWDM2013** dataset consists of data from two events: *(i)* the Joplin collection contains tweets from the tornado that struck Joplin, Missouri on May 22, 2011; *(ii)* The Sandy collection contains tweets collected from Hurricane Sandy that hit Northeastern US on Oct 29, 2012 (Imran et al. 2013a).
4. **ISCRAM2013** dataset consists of tweets from two different events occurred in 2011 (Joplin 2011) and 2012 (Sandy 2012). Note that this set of tweets are different than SWDM2013 set even though they are collected from same events (Imran et al. 2013b).
5. **Disaster Response Data (DRD)** consists of tweets collected during various crisis events that took place in 2010 and 2012. This dataset is annotated using 36 classes that include informativeness as well as humanitarian categories.[4]
6. **Disasters on Social Media (DSM)** dataset comprises 10K tweets collected and annotated with labels *related* vs. *not-related* to the disasters.[5]

[4] https://appen.com/datasets/combined-disaster-response-data/

[5] https://data.world/crowdflower/disasters-on-social-media

Source	Total	Mapping		Filtering	
		Info	Hum	Info	Hum
CrisisLex	88,015	84,407	84,407	69,699	69,699
CrisisNLP	52,656	51,271	50,824	40,401	40,074
SWDM13	1,543	1,344	802	857	699
ISCRAM13	3,617	3,196	1,702	2,521	1,506
DRD	26,235	21,519	7,505	20,896	7,419
DSM	10,876	10,800	0	8,835	0
CrisisMMD	16,058	16,058	16,058	16,020	16,020
AIDR	7,411	7,396	6,580	6,869	6,116

Table 1: Different datasets and their sizes (number of tweets) before and after label mapping and filtering steps. Info: Informativeness, Hum: Humanitarian

7. **CrisisMMD** is a multimodal dataset consisting of tweets and associated images collected during seven disaster events that happened in 2017 (Alam et al. 2018). The annotations for this dataset is targeted for three classification tasks: *(i)* informative *vs.* not-informative, *(ii)* humanitarian categories (eight classes) and *(iii)* damage severity assessment.
8. **AIDR** dataset is obtained from the *AIDR system* (Imran et al. 2014) that has been annotated by domain experts for different events and made available upon requests. We only retained labeled data that are relevant to this study.

First part of Table 1 summarizes original sizes of the datasets. The CrisisLex and CrisisNLP datasets are the largest and second-largest datasets, respectively, which are currently widely used in the literature. The SWDM2013 is the smallest set. However, it is one of the earliest datasets used by the crisis informatics community.

3.2 Class Label Mapping

The datasets come with different class labels. We create a set of common class labels by manually mapping semantically similar labels into one cluster. For example, the label "building damaged," originally used in the AIDR system, is mapped to "infrastructure and utilities damage" in our final dataset. Some of the class labels in these datasets are not annotated for *humanitarian aid*[6] purposes, therefore, we have not included them in the consolidated dataset. For example, we do not select tweets labeled as "animal management" or "not labeled" that appear in CrisisNLP and CrisisLex26. This causes a drop in the number of tweets for both informativeness and humanitarian tasks as can be seen in Table 1 (Mapping column). The large drop in the CrisisLex dataset for the informativeness task is due to the 3,103 unlabeled tweets (i.e., labeled as "not labeled"). The other significant drop for the informativeness task is in the DRD dataset. This is because many tweets were annotated with multiple labels, which we have not included in our consolidated dataset. The reason is to reduce additional manual effort as it requires relabeling them for multiclass setting. Moreover, many tweets in these datasets were labeled for informativeness only. For

[6] https://en.wikipedia.org/wiki/Humanitarian_aid

example, the DSM dataset is only labeled for informativeness, and a large portion of the DRD dataset is labeled for informativeness only. We could not map them for the humanitarian task.

3.3 Exact- and Near-Duplicate Filtering

To develop a machine learning model, it is important to design non-overlapping train/dev/test splits. A common practice is to randomly split the dataset into train/dev/test sets. This approach does not work with social media data as it generally contains duplicates and near duplicates. Such duplicate content, if present in both train and test sets, often leads to overestimated test results during classification. Filtering the near-and-exact duplicate content is one of the major steps we have taken into consideration while consolidating the datasets.

We first tokenize the text before applying any filtering. For tokenization, we used a modified version of the Tweet NLP tokenizer (O'Connor, Krieger, and Ahn 2010).[7] Our modification includes lowercasing the text and removing URL, punctuation, and user id mentioned in the text. We then filter tweets having only one token. Next, we apply exact string matching to remove exact duplicates. An example of an exact duplicate tweet is: "*RT Reuters: BREAKING NEWS: 6.3 magnitude earthquake strikes northwest of Bologna, Italy: USGS*", which appear three times with exact match in CrisisLex26 (Olteanu et al. 2014) dataset that has been collected during Northern Italy Earthquakes, 2012.[8]

Then, we use a similarity-based approach to remove the near-duplicates. To do this, we first convert the tweets into vectors using bag-of-ngram approach as a vector representation. We use uni- and bi-grams with their frequency-based representations. We then use cosine similarity to compute a similarity score between two tweets and flag them as *duplicate* (e.g., first tweet in Table 2) if their similarity score is greater than the threshold value of 0.75. In the similarity-based approach, threshold selection is an important aspect. Choosing a lower value would remove many distant tweets while choosing a higher value would leave several near-duplicate tweets in the dataset. To determine a plausible threshold value, we manually checked the tweets in different threshold bins (i.e., 0.70 to 1.0 with 0.05 interval) as shown in Figure 1, which we selected from consolidated informativeness dataset. By investigating the distribution and manual checking, we concluded that a threshold value of 0.75 is a reasonable choice. From the figure we can clearly see that choosing a lower threshold (e.g., < 0.75) removes larger number of tweets. Note that rest of the tweets have similarity lower than what we have reported in the figure. In Table 2, we provide a few examples for the sake of clarity.

We analyzed the data to understand which events and datasets have more exact- and near-duplicates. Figure 2 provides counts for both exact- and near-duplicates for informativeness tweets. In the figure, we report total number (in parenthesis the number represents percentage of reduction)

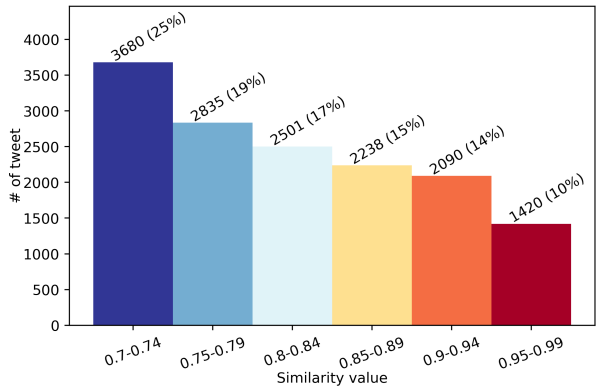

Figure 1: Number of near-duplicates in different bins obtained from consolidated informativeness tweets after label mapping. Tweets will lower similarity (< 0.7) bins are not reported here.

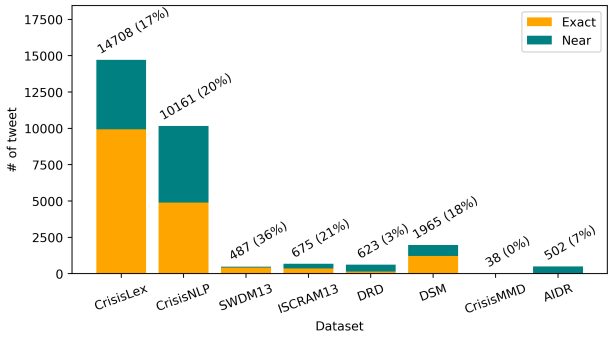

Figure 2: Exact- and near-duplicates in informativeness tweets. Number on top of each bar represents total number, and the number in the parenthesis represents percentage.

of duplicates (i.e., exact and near) for each dataset. The CrisisLex and CrisisNLP have higher number of duplicates comparatively, however, it is because those two are relatively larger in size. For each of these datasets, we analyzed different events where duplicates appear most. In CrisisLex, the majority of the exact duplicates appear in "Queensland floods (2013)"[9] consisting of 2270 exact duplicates. The second majority is "West Texas explosion (2013)" event, which consists of 1301 duplicates. Compared to CrisisLex, the exact duplicates are low in CrisisNLP, and the majority of such duplicates appear in the "Philippines Typhoon Hagupit (2014)" event with 1084 tweets. For the humanitarian tweets, we observed a similar trend.

As indicated in Table 1, there is a drop after filtering, e.g., ∼25% for informativeness and ∼20% for humanitarian tasks. It is important to note that failing to eradicate duplicates from the consolidated dataset would potentially lead to misleading performance results in the classification experiments.

[7] https://github.com/brendano/ark-tweet-nlp

[8] http://en.wikipedia.org/wiki/2012_Northern_Italy_earthquakes

[9] Event name refers to the event during which data has been collected by the respective data authors (see Section 3.1).

#	Tweet	Tokenized	Sim.	Dup.
1	Live coverage: Queensland flood crisis via @Y7News http://t.co/Knb407Fw *Live coverage: Queensland flood crisis - Yahoo!7 http://t.co/U2hw0LWW via @Y7News*	live coverage queensland flood crisis via url *live coverage queensland flood crisis yahoo url via*	0.788	✓
2	"@guardian: Queensland counts flood cost as New South Wales braces for river peaks http://t.co/MpQskYt1". Brisbane friends moved to refuge. *Queensland counts flood cost as New South Wales braces for river peaks http://t.co/qb5UuYf9*	queensland counts flood cost as new south wales braces for river peaks url brisbane friends moved to refuge *queensland counts flood cost as new south wales braces for river peaks url*	0.778	✓
3	RT @FoxNews: #BREAKING: Numerous injuries reported in large explosion at #Texas fertilizer plant http://t.co/oH93niFiAS". Brisbane friends moved to refuge. *Numerous injuries reported in large explosion at Texas fertilizer plant: DEVELOPING: Emergency crews in Texas ... http://t.co/Th5Yzvdg5m*	rt breaking numerous injuries reported in large explosion at texas fertilizer plant url *numerous injuries reported in large explosion at texas fertilizer plant developing emergency crews in texas url*	0.744	✗

Table 2: Examples of near-duplicates with similarity scores selected from informativeness tweets. Near-duplicates are in italic form. Sim. refers to similarity value. Dup. refers to whether we consider them as duplicate. The symbol (✓) indicates a duplicate, which we dropped, and the symbol (✗) indicates a non-duplicate, which we kept in our dataset.

3.4 Adding Language Tags

Some of the existing datasets contain tweets in various languages (i.e., Spanish and Italian) without explicit assignment of a language tag. In addition, many tweets have code-switched (i.e., multilingual) content. For example, the following tweet has both English and Spanish text: *"It's #Saturday, #treat yourself to our #Pastel tres leches y compota de mora azul. https://t.co/WMpmu27P9X"*. Note that Twitter tagged this tweet as English whereas the Google language detector service tagged it as Spanish with a confidence score of 0.379.

We decided to provide a language tag for each tweet if it is not available with the respective dataset. We used the language detection API of Google Cloud Services[10] for this purpose. In Figure 3, we report language distribution for the top nineteen languages consists of more than 20 tweets. Among different languages of informativeness tweets, English tweets appear to be highest in the distribution compared to any other language, which is 94.46% of 156,899. Note that most of the non-English tweets appear in the CrisisLex dataset. We believe our language tags will enable future studies to perform multilingual analysis.

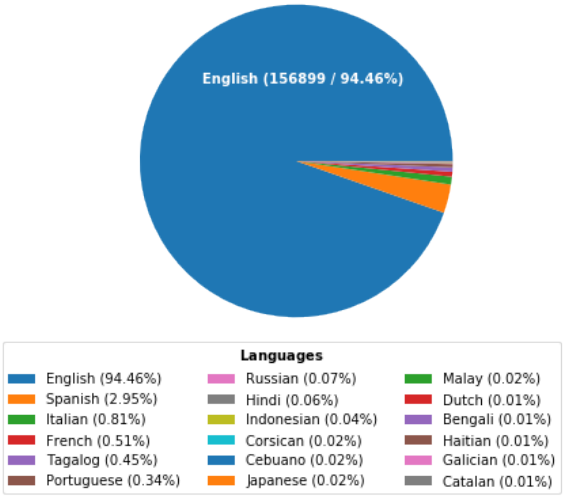

Figure 3: Distribution of top nineteen languages (>= 20 tweets) in the consolidated informativeness tweets.

3.5 Data Statistics

Distribution of class labels is an important factor for developing the classification model. In Table 3 and 4, we report individual datasets along with the class label distribution for informativeness and humanitarian tasks, respectively. It is clear that there is an imbalance in class distributions in different datasets and some class labels are not present. For example, the distribution of "not informative" class is very low in SWDM2013 and ISCRAM2013 datasets. For the humanitarian task, some class labels are not present in different datasets. Only 17 tweets with the label "terrrorism related" are present in CrisisNLP. Similarly, the class "disease related" only appears in CrisisNLP. The scarcity of the class labels poses a great challenge to design the classification model using individual datasets. Even after combining the datasets, the imbalance in class distribution seems to persist (last column in Table 4). For example, the distribution of "not humanitarian" is relatively higher (37.40%) than other class labels. In Table 4, we report some class labels (highlighted in italic), which we dropped in the rest of the classification experiments conducted in this study. However, tweets with those class labels will be available in the released datasets. The reason for not including them in the experiments is that we aim to develop classifiers for the disaster response tasks only.

[10] https://cloud.google.com/translate/docs/advanced/detecting-language-v3. Note, it is a paid service, therefore, we have not used this service for the tweets for which language tags are available.

Class	CrisisLex	CrisisNLP	SWDM13	ISCRAM13	DRD	DSM	CrisisMMD	AIDR	Total
Informative	42,140	23,694	716	2,443	14,849	3,461	11,488	2,968	101,759
Not informative	27,559	16,707	141	78	6,047	5,374	4,532	3,901	64,339
Total	**69,699**	**40,401**	**857**	**2,521**	**20,896**	**8,835**	**16,020**	**6,869**	**166,098**

Table 3: Data (tweets containing multiple languages) distribution of informativeness across different sources.

Class	CrisisLex	CrisisNLP	SWDM13	ISCRAM13	DRD	CrisisMMD	AIDR	Total
Affected individual	3,740	-	-	-	-	471	-	4,211
Caution and advice	1,774	1,137	117	412	-	-	161	3,601
Disease related	-	1,478	-	-	-	-	-	1,478
Displaced and evacuations	-	495	-	-	-	-	50	545
Donation and volunteering	1,932	2,882	27	189	10	3,286	24	8,350
Infrastructure and utilities damage	1,353	1,721	-	-	877	1,262	283	5,496
Injured or dead people	-	2,151	139	125	-	486	267	3,168
Missing and found people	-	443	-	43	-	40	46	572
Not humanitarian	27,559	16,708	142	81	-	4,538	3,911	52,939
Other relevant information	29,562	8,188	-	-	-	5,937	939	44,626
Personal update	-	116	274	656	-	-	-	1,046
Physical landslide	-	538	-	-	-	-	-	538
Requests or needs	-	215	-	-	6,532	-	257	7,004
Response efforts	-	1,114	-	-	-	-	-	1,114
Sympathy and support	3,779	2,872	-	-	-	-	178	6,829
Terrorism related	-	16	-	-	-	-	-	16
Total	**69,699**	**40,074**	**699**	**1,506**	**7,419**	**16,020**	**6,116**	**141,533**

Table 4: Data (tweets containing multiple languages) distribution of humanitarian categories across different datasets.

4 Experiments

Although our consolidated dataset contains multilingual tweets, we only use tweets in English language in our experiments. We split data into train, dev, and test sets with a proportion of 70%, 10%, and 20%, respectively, also reported in Table 5. As mentioned earlier we have not selected the tweets with highlighted (in italic form) class labels in Table 4 for the classification experiments. Therefore, in this and next Section 5 we report the class label distribution and results on the selected class labels with English tweets only.

4.1 Models and Architectures

In this section, we describe the details of our classification models. For the experiments, we use CNN, fastText, and pre-trained transformer models.

CNN: The current state-of-the-art disaster classification model is based on the CNN architecture. We used similar architecture as proposed by (Nguyen et al. 2017).

fastText: For the fastText (Joulin et al. 2017), we used pre-trained embeddings trained on Common Crawl, which is released by fastText for English.

Transformer models: Pre-trained models have achieved state-of-the-art performance on natural language processing tasks and have been adopted as feature extractors for solving down-stream tasks such as question answering, and sentiment analysis. Though the pre-trained models are mainly trained on non-Twitter text, we hypothesize that their rich contextualized embeddings would be beneficial for the disaster domain. In this work, we choose the pre-trained models BERT (Devlin et al. 2019), DistilBERT (Sanh et al. 2019), and RoBERTa (Liu et al. 2019) for the classification tasks.

Model Settings: We train the CNN models using the Adam optimizer (Kingma and Ba 2014). The batch size is 128 and maximum number of epochs is set to 1000. We use a filter size of 300 with both window size and pooling length of 2, 3, and 4, and a dropout rate 0.02. We set *early stopping* criterion based on the accuracy of the development set with a patience of 200. For the experiments with fastText, we used default parameters except: *(i)* the dimension is set to 300, *(ii)* minimal number of word occurrences is set to 3, and *(iii)* number of epochs is 50. We train transformers models using the Transformer Toolkit (Wolf et al. 2019). For each model, we use an additional task-specific layer. We fine-tune the model using fine-tuning procedure as prescribed by (Devlin et al. 2019). Due to the instability of the pre-trained models as reported in (Devlin et al. 2019), we perform ten re-runs for each experiment using different seeds, and we select the model that performs best on the dev set. For transformer-based models, we used a learning rate of $2e-5$, and a batch size of 8. More details of the parameters setting can be found in the released scripts.

4.2 Preprocessing and Evaluation

Preprocessing: Prior to the classification experiment, we preprocess tweets to remove symbols, emoticons, invisible and non-ASCII characters, punctuations (replaced with whitespace), numbers, URLs, and hashtag signs.

Informativeness	Train	Dev	Test	Total
Informative	65826	9594	18626	94046
Not informative	43970	6414	12469	62853
Total	**109796**	**16008**	**31095**	**156899**
Humanitarian				
Affected individual	2454	367	693	3514
Caution and advice	2101	309	583	2993
Displaced and evacuations	359	53	99	**511**
Donation and volunteering	5184	763	1453	7400
Infrastructure and utilities damage	3541	511	1004	5056
Injured or dead people	1945	271	561	2777
Missing and found people	373	55	103	**531**
Not humanitarian	36109	5270	10256	51635
Requests or needs	4840	705	1372	6917
Response efforts	780	113	221	**1114**
Sympathy and support	3549	540	1020	5109
Total	**61235**	**8957**	**17365**	**87557**

Table 5: Data split and their distributions with the consolidated English tweets dataset.

Evaluation: To measure the performance of each classifier, we use weighted average precision (P), recall (R), and F1-measure (F1). The rationale behind choosing the weighted metric is that it takes into account the class imbalance problem.

4.3 Experimental Settings

Individual vs. Consolidated Datasets: The motivation of these experiments is to investigate whether model trained with consolidated dataset generalizes well across different sets. For the individual dataset classification experiments, we selected CrisisLex and CrisisNLP as they are relatively larger in size and have a reasonable number of class labels, i.e., six and eleven class labels, respectively. Note that these are subsets of the consolidated dataset reported in Table 5. We selected them from train, dev and test splits of the consolidated dataset to be consistent across different classification experiments. To understand the effectiveness of the smaller datasets, we run experiments by training the model using smaller datasets and evaluating using the consolidated test set.

Event-aware Training The availability of annotated data for a disaster event is usually scarce. One of the advantages of our compiled data is to have identical classes across several disaster events. This enables us to combine the annotated data from all previous disasters for the classification. Though this increases the size of the training data substantially, the classifier may result in sub-optimal performance due to the inclusion of heterogeneous data (i.e., a variety of disaster types and occurs in a different part of the world). Sennrich, Haddow, and Birch (2016) proposed a tag-based strategy where they add a tag to machine translation training data to force a specific type of translation. The method has later been adopted to do domain adaptation and multilingual machine translation (Chu, Dabre, and Kurohashi 2017; Sajjad et al. 2017). Motivated by it, we propose an event-aware training mechanism. Given a set of m disaster event types $\mathbf{D} = \{d_1, d_2, ..., d_m\}$ where disaster event type d_i includes earthquake, flood, fire, and hurricane. For a disaster event type d_i, $\mathbf{T_i} = \{t_1, t_2, ..., t_n\}$ are the annotated tweets. We append a disaster event type as a token to each annotated tweet t_i. More concretely, say tweet t_i consists of k words $\{w_1, w_2, ..., w_k\}$. We append a disaster event type tag d_i to each tweet so that t_i would become $\{d_i, w_1, w_2, ..., w_k\}$. We repeat this step for all disaster event types present in our dataset. We concatenate the modified data of all disasters and use it for the classification.

The event-aware training requires the knowledge of the disaster event type at the time of the test. If we do not provide a disaster event type, the classification performance will be suboptimal due to a mismatch between train and test. To apply the model to an unknown disaster event type, we modify the training procedure. Instead of appending the disaster event type to all tweets of a disaster, we randomly append disaster event type `UNK` to 5% of the tweets of every disaster. Note that `UNK` is now distributed across all disaster event types and is a good representation of an unknown event.

5 Results and Discussions

5.1 Individual vs. Consolidated Datasets

In Table 6, we report the classification results for individual vs. consolidated datasets for both informativeness and humanitarian tasks using the CNN model. As mentioned earlier, we selected CrisisLex and CrisisNLP to conduct experiments for the individual datasets. The model trained with individual dataset shows that performance is higher on the corresponding set but low on other sets. For example, for informativeness task, the model trained with CrisisLex performs better on CrisisLex but not on CrisisNLP and Consolidated sets. We see similar pattern for CrisisNLP. However, the model trained with Consolidated data shows similar performance as individual sets (i.e., CrisisLex and CrisisNLP) but higher on consolidated set. A comparison is shown in the Table 6. The model trained using the consolidated dataset achieves 0.866 (F1) for informativeness and 0.829 for humanitarian, which is better than the models trained using individual datasets. This proves that model with consolidated dataset generalizes well, obtaining similar performance on individual sets and higher on the consolidated set.

Between CrisisLex and CrisisNLP, the performance is higher on CrisisLex dataset for both informativeness and humanitarian tasks (1st *vs.* 4th row in Table 6 for the informativeness, and 10th *vs.* 13th row for the humanitarian task in the same table.). This might be due to the CrisisLex dataset being larger than the CrisisNLP dataset. The cross dataset (i.e., train on CrisisLex and evaluate on CrisisNLP) results shows that there is a drop in performance. For example, there is 14.3% difference in F1 on CrisisNLP data using the CrisisLex model for the informativeness task. Similar behavior observed when evaluated the CrisisNLP model on the CrisisLex dataset. In the humanitarian task, for different datasets in Table 6, we have different number of class labels. We report the results of those classes only for which the model is able to classify. For example, the model trained using the CrisisLex data can classify tweets using one of the

Train	Test	Acc	P	R	F1
Informativeness					
CLex (2C)	1. CLex	0.945	0.945	0.950	0.945
	2. CNLP	0.689	0.688	0.690	0.689
	3. Conso	0.801	0.807	0.800	0.803
CNLP (2C)	4. CNLP	0.832	0.832	0.830	0.832
	5. CLex	0.712	0.803	0.710	0.705
	6. Conso	0.725	0.768	0.730	0.727
Conso (2C)	7. CLex	0.943	0.943	0.940	0.943
	8. CNLP	0.829	0.828	0.830	0.828
	9. Conso	0.867	0.866	0.870	***0.866***
Humanitarian					
CLex (6C)	10. CLex	0.921	0.920	0.920	0.920
	11. CNLP	0.554	0.546	0.550	0.544
	12. Conso	0.694	0.601	0.690	0.633
CNLP (10C)	13. CNLP	0.780	0.757	0.780	0.762
	14. CLex	0.769	0.726	0.770	0.714
	15. Conso	0.666	0.582	0.670	0.613
Conso (11C)	16. CLex	0.908	0.916	0.910	0.912
	17. CNLP	0.768	0.753	0.770	0.753
	18. Conso	0.835	0.827	0.840	***0.829***

Table 6: Classification results using CNN for the individual and consolidated datasets. CLex: CrisisLex, CNLP: CrisisNLP, Conso: Consolidated; 6C, 10C, and 11C refer to six, ten and eleven class labels respectively.

Train	Test	CNN	FT	BERT	D-B	RT
Informativeness						
CLex (2C)	1. CLex	0.945	0.940	0.949	0.949	0.938
	2. CrisisNLP	0.689	0.687	0.698	0.681	0.694
	3. Conso	0.803	0.791	0.806	0.808	0.810
CNLP (2C)	4. CNLP	0.832	0.816	0.833	0.834	0.823
	5. CLex	0.705	0.728	0.749	0.739	0.726
	6. Conso	0.727	0.733	0.753	0.755	0.744
Conso (2C)	7. CLex	0.943	0.917	0.940	0.938	0.946
	8. CNLP	0.828	0.811	0.825	0.828	0.829
	9. Conso	0.866	0.844	0.872	0.870	***0.883***
Humanitarian						
CLex (6C)	10. CLex	0.920	0.911	0.934	0.935	0.937
	11. CNLP	0.544	0.549	0.615	0.628	0.632
	12. Conso	0.633	0.605	0.766	0.770	0.784
CNLP (10C)	13. CNLP	0.762	0.759	0.791	0.788	0.789
	14. CLex	0.714	0.719	0.842	0.845	0.850
	15. Conso	0.613	0.627	0.709	0.707	0.727
Conso (11C)	16. CLex	0.912	0.903	0.923	0.921	0.931
	17. CNLP	0.753	0.760	0.786	0.787	0.784
	18. Conso	0.829	0.824	0.860	0.856	***0.872***

Table 7: Classification results (weighted-F1) using CNN, fastText (FT) and transformer based models. D-B: DistilBERT, RT: RoBERTa.

six class labels (see Table 4 for excluded labels with highlights). The experiments with smaller datasets for both informativeness and humanitarian tasks show the importance of designing a classifier using a larger dataset. Note that humanitarian task is a multi-class classification problem, which makes it a much more difficult task than the binary informativeness classification.

Comparing Models: In Table 7, we report the results using CNN, fastText and transformer based models. We report weighted F1 for all models and tasks. The transformer based models achieve higher performance compared to the CNN and fastText. We used three transformer based models, which varies in the parameter sizes. However, in terms of performance, they are quite similar.

Class-wise Results Analysis: In Table 8, we report class-wise performance of both CNN and BERT models for the humanitarian task. BERT performs better than or on par with CNN across all classes. More importantly, BERT performs substantially better than CNN in the case of minority classes as highlighted, in italic form, in the table. We further investigate the classification results of the CNN models for the minority class labels. We observe that the class "response efforts" is mostly confused with "donation and volunteering" and "not humanitarian". For example, the following tweet with "response efforts" label, *"I am supporting Rebuild Sankhu @crowdfunderuk #crowdfunder http://t.co/WBsKGZHHSj"*, is classified as "donation and volunteering". We also observe similar phenomena in minority class labels. The class "displaced and evacuations" is confused with "donation and volunteering" and "caution and advice". It is interesting that the class "missing and found people" is confused with "donation and volunteering" and "not humanitarian". The following "missing and found people" tweet, *"RT @Fahdhusain: 11 kids recovered alive from under earthquake rubble in Awaran. Shukar Allah!!"*, is classified as "donation and volunteering".

5.2 Event-aware

In Table 9, we report the results of the event-aware training using both CNN and BERT. The event-aware training improves the classification performance by 1.3 points (F1) using CNN for the humanitarian task compared to the results without using event information (see Table 6). However, no improvement has been observed for the informativeness task. The training using event information enables the system to use data of all disasters while preserving the disaster-specific distribution. Event-aware training is also effective in the advent of a new disaster event. Based on the type of a new disaster, one may use appropriate tags to optimize the classification performance. The event-aware training can be extended to use more than one tags. For example, in addition to preserving the event information, one can also append a tag for the disaster region. In this way, one can optimize the model for more fine-grained domain information. The event-aware training with BERT does not provide better results in any of the tasks, which requires further investigation and we leave it as a future study.

5.3 Discussions

Social media data is noisy and it often poses a challenge for labeling and training classifiers. Our analysis on publicly available datasets reveals that one should follow a number of steps before preparing and labeling any social media

Class	CNN			BERT		
	P	R	F1	P	R	F1
Affected individual	0.760	0.720	0.740	0.752	0.808	0.779
Caution and advice	0.630	0.630	0.630	0.675	0.707	0.691
Displaced and evacuations	0.490	0.180	0.260	0.491	0.535	0.512
Donation and volunteering	0.700	0.790	0.740	0.764	0.807	0.785
Infra. and util. damage	0.650	0.660	0.660	0.696	0.717	0.706
Injured or dead people	0.760	0.780	0.770	0.812	0.845	0.828
Missing and found people	0.470	0.170	0.240	0.457	0.466	0.462
Not humanitarian	0.900	0.930	0.920	0.934	0.920	0.927
Requests or needs	0.850	0.840	0.850	0.909	0.901	0.905
Response efforts	0.330	0.070	0.120	0.349	0.308	0.327
Sympathy and support	0.760	0.640	0.690	0.751	0.725	0.738

Table 8: Class-wise classification results of humanitarian task on the consolidated dataset using CNN and BERT.

Model	Informativeness			Humanitarian		
	P	R	F1	P	R	F1
CNN	0.868	0.870	0.867	0.841	0.850	0.842
fastText	0.824	0.824	0.824	0.794	0.795	0.794
BERT	0.872	0.872	**0.872**	0.866	0.865	0.865
DistilBERT	0.874	0.875	**0.874**	0.863	0.864	0.863
RoBERTa	0.879	0.879	**0.878**	0.871	0.870	**0.870**

Table 9: Results of event-aware experiments using the consolidated dataset.

dataset, not just the dataset for crisis computing. Such steps include *(i)* tokenization to help in the subsequent phase, *(ii)* remove exact- and near-duplicates, *(iii)* check for existing data where the same tweet might be annotated for the same task, and then *(iv)* labeling. For designing the classifier, we postulate checking the overlap between training and test splits to avoid any misleading performance.

The classification performance that we report is considered as benchmark results, which can be used to compare in any future study. The current state-of-art for informativeness and humanitarian tasks can be found in (Burel et al. 2017; Alam, Muhammad, and Ferda 2019; Alam et al. 2021). The F-measure for informativeness and humanitarian tasks are reported as 0.838 and 0.613, respectively, on the CrisisLex26 dataset in (Burel et al. 2017). Whereas in (Alam, Muhammad, and Ferda 2019), the reported F-measure for informativeness and humanitarian tasks are 0.93 and 0.78, respectively. It is important to emphasize the fact that the results reported in this study are reliable as they are obtained on a dataset that has been cleaned from duplicate content, which might have led to misleading performance results otherwise. The recent results reported in (Alam et al. 2021) shows a best F-measure of 0.781 for humanitarian task, which can be comparable with this study.

Our initial consolidated datasets (i.e., Table 3 and 4) contains multilingual content with more class labels and different types of content (e.g., disease-related), therefore, an interesting future research could be to try different pretrained multilingual models to classify tweets in different languages. We have run a set of preliminary experiments using our initial consolidated datasets, and using monolingual model such as CNN, fastText, BERT, DistilBERT,

Model	Informativeness			Humanitarian		
	P	R	F1	P	R	F1
Monolingual						
CNN	0.827	0.828	0.828	0.650	0.647	0.648
FastText	0.820	0.821	0.820	0.662	0.663	0.662
BERT	0.872	0.873	0.872	0.771	0.772	0.771
DistilBERT	0.871	0.872	0.871	0.770	0.771	0.770
RoBERTa	0.879	0.880	0.879	0.785	0.784	0.784
Multilingual						
BERT-m	0.879	0.879	0.879	0.783	0.781	0.781
DistilBERT-m	0.872	0.873	0.872	0.771	0.772	0.771
XLM-RoBERTa	0.879	0.879	0.879	0.789	0.788	0.788

Table 10: Results of consolidated (multilingual) datasets (class label distributions are reported in Table 3 and 4) for both tasks and different mono and multilingual models. BERT-m: bert-base-multilingual-uncased, DistilBERT-m: distilbert-base-multilingual-cased

RoBERTa, and multilingual versions of the mentioned transformer models. The results are reported in Table 10. We observe that performance dropped significantly for the humanitarian task compared to English-only dataset. For example, $\sim$8% drop using BERT model. Note that test set for English tweets (Table 5) is a subset of this set of tweets. From the results of multilingual versions of BERT (BERT-m), we see that there is an increase in performance compared to other mono-lingual models, however, the results are still far below. Such a finding shows an interesting avenue for further research. Another future research direction would be to use multilingual models for the zero-shot classification of tweets.

The competitive performance of transformer based models encourages us to try deeper models such as Google T5 (Raffel et al. 2020). For the transformer based model, it is important to invest the effort to try different regularization methods to obtain better results, which we foresee as a future study.

Our released dataset and benchmark results will help the research community to develop better models and compare results. The inclusion of language tags can help to conduct multilingual experiments. The resulting dataset covers a time-span starting from 2010 to 2017, which can be used to study temporal aspects in crisis scenarios.

6 Conclusions

The information available on social media has been widely used by humanitarian organizations at times of a disaster. Many techniques and systems have been developed to process social media data. However, the research community lacks a standard dataset and benchmarks to compare the performance of their systems. We tried to bridge this gap by consolidating existing datasets, filtering exact- and near-duplicates, and providing benchmarks based on state-of-the-art CNN, FastText, and transformer-based models. Our experimental results and data splits can be useful for future research to conduct multilingual studies, developing new models and cross-domain experiments.

Broader Impact

The developed consolidated labeled dataset is curated from different publicly available sources. The consolidated labeled dataset can be used to develop models for humanitarian response tasks and can be useful to fast responders. We release the dataset by maintaining the license of existing resources.

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