MEDIC: a multi-task learning dataset for disaster image classification

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Abstract
Recent research in disaster informatics demonstrates a practical and important use case of artificial intelligence to save human lives and suffering during natural disasters based on social media contents (text and images). While notable progress has been made using texts, research on exploiting the images remains relatively under-explored. To advance image-based approaches, we propose MEDIC (https://crisisnlp.qcri.org/medic/index.html), which is the largest social media image classification dataset for humanitarian response consisting of 71,198 images to address four different tasks in a multi-task learning setup. This is the first dataset of its kind: social media images, disaster response, and multi-task learning research. An important property of this dataset is its high potential to facilitate research on multi-task learning, which recently receives much interest from the machine learning community and has shown remarkable results in terms of memory, inference speed, performance, and generalization capability. Therefore, the proposed dataset is an important resource for advancing image-based disaster management and multi-task machine learning research. We experiment with different deep learning architectures and report promising results, which are above the majority baselines for all tasks. Along with the dataset, we also release all relevant scripts (https://github.com/firojalam/medic).

Keywords Multi-task learning • Social media images • Image classification • Natural disasters • Crisis informatics • Deep learning • Dataset

1 Introduction
Natural disasters cause significant damage (e.g., Hurricane Harvey in 2017 cost $125 billion)1 and require urgent assistance in time of crisis. In the last decade, various social media played important roles in humanitarian response tasks as they were widely used to disseminate information and obtain valuable insights. During disaster events, people post content (e.g., text, images, and video) on social media to ask for help (e.g., report of a person stuck on a rooftop during a flood), offer support, identify urgent needs, or share their feelings. Such information is helpful for humanitarian organizations to take immediate actions to plan and launch relief operations. Recent studies demonstrated that images shared on social media during a disaster can assist humanitarian organizations in recognizing damages in infrastructure [1], assessing damage severity [2], identifying humanitarian information [3], detecting crisis incidents [4], and detecting disaster events with other related tasks [5]. However, the amount of

1 https://en.wikipedia.org/wiki/List_of_disasters_by_cost.
research and resources to develop powerful computer vision-based predictive models remains insufficient compared to the NLP-based progress [6–8]. Motivated by these observations, this research aims to enrich available resources to make further advancements in the computer vision-based disaster management studies.

Recent advances in deep convolutional neural networks (CNN) and their learning techniques provide efficient solutions for different computer vision applications. While simple applications can be realized with a single-task formulation such as classification [9], semantic segmentation [10], or object detection [11], the complex ones such as autonomous vehicles, robotics, and social media image analysis [12, 13] necessitate incorporating multiple tasks, which significantly increases the computational and memory requirements for both training and inference. Multi-task learning (MTL) techniques [13–15] have emerged as the standard approach for these complex applications where a model is trained to solve multiple tasks simultaneously, which helps to improve the performance, reduce inference time and computational complexities. For example, an image posted on social media during a disaster event may contain information whether it is a flood event, shows infrastructure damage, and is severe. Such a multitude of information needs to be detected in real-time to help humanitarian organizations [12, 16] with various tasks including (i) disaster type recognition, (ii) informativeness classification, (iii) humanitarian categorization, and (iv) damage severity assessment (see Sect. 3 for more details).

Existing works [1–3] present separate task-specific models, resulting in higher computational complexities (e.g., computational power, training and inference time). Hence, this research aims at reducing this overhead by addressing different tasks simultaneously with an MTL setup, which can also help reduce the carbon footprint [17].

Labeled public image datasets, such as ImageNet [18] and Microsoft COCO [19] made significant contributions to the advancement of today’s powerful machine learning models. Likewise, for the MTL setup, several image datasets have already been proposed, which are summarized in Table 1. These datasets include images from different domains such as indoor scenes, driving, faces, handwritten digits, and animal recognition, which are already contributing to the advancement of MTL research. However, an MTL dataset for critical real-world applications which comprise humanitarian response tasks during natural disasters is yet to become available. This paper proposes a novel MTL dataset for disaster image classification.

To this end, we build upon the previous work of Alam et al. [5] where the images are mostly annotated for individual tasks, and only 5558 out of 71,198 images have labels for all four tasks mentioned above. We provide an expansive extension by annotating the images for all tasks, i.e., we annotated 155,899 more labels for these tasks in addition to the existing ones. For disaster type recognition and humanitarian categorization tasks, we also labeled a part of the images with multiple labels following a weak supervision approach as they are suitable for multilabel annotation (see Sect. 3). Figure 1 shows example images with the labels for all four tasks.

Our contributions in this research can be summarized as follows: (i) we provide a social media MTL image dataset for disaster response tasks with various complexities, which can be used as an evaluation benchmark for computer vision research; (ii) we ensured high quality annotations by making sure that at least two annotators agree on a label; (iii) we provide a benchmark for heterogeneous multi-task learning and baseline studies to facilitate future study; (iv) our experimental results can also be used as a baseline in the single-task learning setting.

The rest of the paper is organized as follows. Section 2 provides an overview of the existing work. Section 3 introduces the tasks and describes the dataset development process. Section 4 explains the experiments and presents the results while Sect. 5 provides a discussion. Finally, we conclude the paper in Sect. 6.

## 2 Related work

This paper mainly focuses on the development of an MTL dataset for disaster response tasks. Therefore, we first review the recent work on MTL and available MTL datasets; and then, survey social media image classification literature and datasets for disaster response.

### 2.1 Multi-task learning and datasets

Multi-task learning (MTL) aims to improve generalization capability by leveraging information in the training data consisting of multiple related tasks [14]. It simultaneously learns multiple tasks and has shown promising results in terms of generalization, computation, memory footprint, performance, and inference time by jointly learning through a shared representation [14, 15]. Since the seminal work by Caruana [14], MTL research has received wide attention in the last several years in NLP, computer vision, and other research areas [15, 20–23]. MTL brings benefits when associated tasks share complementary information. However, performance can suffer when multiple tasks have conflicting needs, and the tasks have competing priorities (i.e., one is superior to the other). This phenomenon is referred to as negative transfer. This understanding led to

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2 For four tasks, 71,198 images now have 284,792 labels whereas previous annotations comprised only 128,893 labels.
Table 1 Upper part of the table presents the datasets used in multi-task learning studies in computer vision research

| Refs. | Dataset | Source | Size | Task type | # Tasks | Tasks | # Classes | Domain | Year |
|-------|---------|--------|------|-----------|---------|-------|----------|--------|------|
| [15]  | PASCAL  | Flickr | 12,030 (I) | Hete. | 5 | SS, HS, SE, and SD | – | Diverse objects | 2021 |
| [15]  | NYU-V2  | PC     | 1449 (I) | Hete. | 3 | IS, SS, and SC | – | Indoor video | 2021 |
| [13]  | BDD100K| Nexar  | 100,000 (V) | Hete. | 10 | Ten tasks | a | Driving | 2020 |
| [24]  | MNIST   | –      | 70,000 (I) | Homo. | 10 | 10 digits cls. | 10 CL. | Handwritten | 2019 |
| [24]  | CIFAR10 | –      | 60,000 (I) | Homo. | 10 | 10 animal cls. | 10 CL. | Animal | 2019 |
| [24]  | UCSD-Birds | –   | 11,788 (I) | Homo. | 10 | 10 R/tasks | Ranking | Animal | 2019 |
| [24]  | OmniGlot| –      | 1,623 (I) | Homo. | 50 | 50 alphabets | 50 CL. | Handwritten | 2019 |
| [24]  | OmniArt | –      | 133,000 (S) | Hete. | 7 | 7 tasks | – | Artwork | 2019 |
| [44]  | Taskonomy| IC     | 4M (I) | Hete. | 26 | 26 tasks | – | Indoor scenes | 2018 |
| [48]  | Office-caltech | – | 2,533 (I) | Homo. | 4 | Amazon, Webcam, and DSLR, Caltech-256 | 10 CL/task | – | 2017 |
| [48]  | Office-Home | SE     | 15,500 (I) | Homo. | 4 | Artistic, clip art, product, and real-world images | 65 objects | – | 2017 |
| [48]  | b | –      | 2400 (I) | Homo. | 4 | Caltech-256, ImageNet Pascal and Bing | – | Diverse | 2017 |
| [37]  | MNIST   | –      | 70,000 (I) | Homo. | 10 | 10 digits cls. | 10 CL. | Handwritten | 2016 |
| [44]  | AdienceFaces | Flickr | 16,252 (I) (G), 16,139 (A) | Hete. | 2 | Gender, Age | Gender: 2 Age: 8 | Face | 2016 |
| [33]  | USPS    | –      | 2000 (S) | Homo. | 10 | 10 ways/tasks | Digits: 0–9 | Handwritten | 2012 |
| [33]  | MNIST   | –      | 2000 (S) | Homo. | 10 | 10 ways/tasks | Digits: 0–9 | Handwritten | 2012 |
| [32]  | USPS    | –      | 2000 (S) | Homo. | 10 | 10 ways/tasks | Digits: 0–9 | Handwritten | 2011 |
| [32]  | MNIST   | –      | 2000 (S) | Homo. | 10 | 10 ways/tasks | Digits: 0–9 | Handwritten | 2011 |
| [32]  | Animal  | –      | 30,000 (I) | Homo. | 20 | 20 ways/tasks | 20 CL. | Animal | 2011 |

Disaster-related datasets

| Refs. | Dataset | Source | Size | Task type | # Tasks | Tasks | # Classes | Domain | Year |
|-------|---------|--------|------|-----------|---------|-------|----------|--------|------|
| [4]   | Incident| Web, SM | 446,684 (I) | NA | 1 | Incident | 43 | Incidents | 2020 |
| [5]   | CrisisBench. | Web, SM | DT:17,511, Info:59,717, Hum:17,769, DS:34,896 | NA | 4 | DT, Info, Hum, DS | DT: 7, Info: 2, Hum:4, DS:3 | Disaster | 2020 |
| [51]  | xBD     | Satellite | 700,000 | NA | – | Building damage | 4 | – | Disaster | 2019 |
| [52]  | MediaEval | 2018 | SM | 1,654 I/P | NA | 1 | Flood | R. and cls.: 2 CL. | Disaster | 2018 |
| [3]   | CrisisMMD | SM | 18,082 | NA | 3 | Info, Hum, DS | Info: 2, Hum:8, DS:3 | Disaster | 2018 |
| [1]   | DMD     | Web    | 5878 | NA | 1 | Damage | 6 | – | Disaster | 2018 |
| [53]  | DAD     | SM     | ~25,000 | NA | 1 | DS | 3 | – | Disaster | 2017 |
| [54]  | DIRSM   | Flickr | T1: 6600 (I); T2: 462 I/P | NA | 1 | Flood | R, cls.: 2 CL | Disaster | 2017 |

Proposed disaster-related multi-task learning dataset

| Dataset | Source | Size | Task type | # Tasks | Tasks | # Classes | Domain | Year |
|---------|--------|------|-----------|---------|-------|----------|--------|------|
| MEDIC   | SM     | 71,198 (I) | Hete. | 4 | DT, Info, Hum, DS | DT: 7, Info: 2, Hum:4, DS:3 | Disaster | 2021 |

Middle part shows disaster related datasets, and the last row shows our proposed dataset. I: Images, V: Videos, S: Samples, SE: Search engines, SM: Social media, DT: disaster types, Info: Informativeness, Hum: Humanitarian, DS: Damage severity. CL.: number of class labels. Hete.: heterogeneous, Homo: Homogeneous, PC: Personal collection. SS: semantic segmentation, HS: human part segmentation, SE: semantic edge detection of surface normals prediction, SD: saliency detection, IS: instance segmentation, SC: scene classification, IC: Indoor scenes, cls.: classification, R/tasks: Ranking tasks, I/P: image patches

a[http://https://doc.bdd100k.com/format.html#categories]
b[ImageCLEF][http://http://imageclef.org/2014/adaptation]
the question of what, when, and how to share information among tasks [15, 24]. To address these aspects, in the deep learning era, numerous architectures and optimization methods have been proposed. The architectures are categorized into hard and soft parameter sharing. Hard parameter sharing design consists of a shared network followed by task-specific heads [25–27]. In soft parameter sharing, each task has its own set of parameters, and a feature sharing mechanism to deal with cross-task talk [28–30]. In MTL literature, a problem can be formulated in two different ways—homogeneous and heterogeneous [24]. While the homogeneous MTL assumes that each task corresponds to a single output, the heterogeneous MTL assumes each task corresponds to a unique set of output labels [14, 31]. The latter setting uses a neural network using multiple sets of outputs and losses. In this study, we aim to provide a benchmark with our heterogeneous MTL dataset using the hard parameter sharing approach.

Earlier studies such as [32] and [33] mostly exploited the MNIST [34] and USPS [35] datasets for MTL experiments. These datasets were originally designed for single-task classification settings. For example, the widely used MNIST dataset was originally designed for digit classification, and Office-Caltech [36] was designed to categorize images in 31 classes, which are collected from different domains. However, such datasets are used with the homogeneous problem setting of multi-task learning by selecting ten target classes as ten binary classification tasks [24, 33, 37]. Numerous other widely used datasets such as MC-COCO [19] and CelebA [38] have also been used for multi-task learning in the homogeneous problem setting.

Several existing datasets consisting of multiple unique output label sets were studied in the heterogeneous setting. For example, AdienceFaces [39] was designed for gender and age group classification tasks, OmniArt [40] consists of seven tasks, NYU-V2 [41] consists of three tasks, and PASCAL [42, 43] consists of five tasks. Very few datasets were specifically designed for multi-task learning research. Most notable ones are Taskonomy [44] and BDD100K [13]. The Taskonomy dataset consists of four million images of indoor scenes from 600 buildings, and each image was annotated for twenty-six visual tasks. Ground truths of this dataset were obtained programmatically, and knowledge distillation approaches. The BDD100K dataset is a diverse 100K driving video dataset consisting of ten tasks. It was collected from Nexar, where videos are uploaded by the drivers. In Table 1, we provide widely used datasets, which have been used for MTL.

### 2.2 Disaster response studies and datasets

During disaster events, social media content has proven to be effective in facilitating different stakeholders including humanitarian organizations [55]. Alongside, there has been growing research interest in developing computational methods and systems to better analyze and extract actionable information from social media content [7, 56, 57]. Most of such efforts relied on social media content, such as Twitter and Facebook, for humanitarian aid [58, 59]. Given that accessing Facebook data became difficult, the use of

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Fig. 1 Examples of images representing all tasks. **T1:** Disaster types, **T2:** Informativeness, **T3:** Humanitarian, **T4:** Damage severity

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3. [https://www.getnexar.com/](https://www.getnexar.com/)
Twitter content remained more popular. Research studies and resource development have focused on Twitter content due to its instant access to timely multi-modal information (i.e., textual and visual) as such information is crucial for different stakeholders (e.g., governmental and non-governmental organizations) [58, 59]. Notable resources with textual content include the CrisisLex [60], CrisisNLP [61], TREC Incident Streams [62], disaster tweet corpus [63], Arabic Tweet Corpus [64], CrisisBench [65], HumAID [66], and CrisisMMD (text and image) [3, 67]. In the past years, several systems have also been developed and deployed during disaster events [58, 68–70]. One notable system is AIDR [58]4, which has been used during major disaster events to collect and classify tweets, and provide a visual summary.

Earlier research efforts in crisis informatics are mainly focused on textual content analysis [8]. However, lately there has been a growing interest in the imagery content analysis as images posted on social media during disasters can play significant role as reported in many studies [2, 12, 16, 53, 71, 72]. Recent works include categorizing the severity of damage into discrete levels [2, 16, 53] or quantifying the damage severity as a continuous-valued index [73, 74]. Such models were also used in real-time disaster response scenarios by engaging with emergency responders [70]. Other related work includes adversarial networks for data scarcity issues [75, 76]; disaster image retrieval [77]; image classification in the context of bush fire emergency [78]; flood photo screening system [79]; sentiment analysis from disaster image [80]; monitoring natural disasters using satellite images [7, 81]; and flood detection using visual features [82].

Publicly available image datasets include damage severity assessment dataset (DAD) [2], multimodal dataset (CrisisMMD) [3] and damage identification multimodal dataset (DMD) [1]. The first dataset is only annotated for images, whereas the last two are annotated for both text and images. Other relevant datasets are Disaster Image Retrieval from Social Media (DIRSM) [54] and MediaEval 2018 [52]. The dataset reported in [51] was constructed for detecting damage as an anomaly using pre-and post-disaster images. It consists of 700,000 building annotations. A similar and relevant work is the Incidents dataset [4], which consists of 446,684 manually labeled images with 43 incident categories. The Crisis Benchmark Dataset reported in [5] is the largest social media disaster image classification dataset, which is a consolidated version of DAD, CrisisMMD, DMD, and additional labeled images.

In this study, we extended the Crisis Benchmark Dataset to adapt it to an MTL setup. To that end, we assigned images with 155,899 more labels to ensure that the entire dataset contains aligned labels for all the tasks. Additionally, we annotated some images with multiple labels, when appropriate, for humanitarian categorization and disaster type recognition tasks.

3 MEDIC dataset

The MEDIC dataset consists of four different disaster-related tasks that are important for humanitarian aid.5 These tasks are defined based on prior work experience with the humanitarian response organizations such as UN-OCHA and existing literature [3, 6, 12, 58]. In this section, we first provide the details of each task and class labels, and then, discuss the annotation details of the dataset.

3.1 Tasks

Disaster types

During man-made and natural disasters, people post textual and visual content about the current situation, and the real-time social media monitoring system requires to detect an event when ingesting images from unfiltered social media streams. For the disaster scenario, it is important to automatically recognize different disaster types from the crawled social media images. For instance, an image can depict a wildfire, flood, earthquake, hurricane, and other types of disasters. Different categories (i.e., natural, human-induced, and hybrid) and sub-categories of disaster types have been defined in the literature [83]. This research focuses on major disaster events that include (i) earthquake, (ii) fire, (iii) flood, (iv) hurricane, (v) landslide, (vi) other disaster, which covers all other types (e.g., plane, train crash), and (vii) not disaster, which includes the images that do not show any identifiable disasters.

Informativeness

Social media contents are often noisy and contain numerous irrelevant images such as cartoons and advertisements. In addition to this, the clean images that show damaged infrastructure due to flood, fire, or any other disaster events are crucial for humanitarian response tasks. Therefore, it is necessary to eliminate any irrelevant or redundant content to facilitate crisis responders’ efforts more effectively. For this purpose, we define the informativeness task as to filter out irrelevant images, where the class labels comprise (i) informative and (ii) not informative.

Humanitarian

Fine-grained categorization of certain information significantly helps the emergency crisis responders to make an efficient actionable decision. Humanitarian categories vary

4 http://aidr.qcri.org/.

5 https://en.wikipedia.org/wiki/Humanitarian_aid.
depending on the type of content (text vs. image). For example, the CrisisBench dataset [65] consists of tweets labeled with 11 categories, whereas CrisisMMD [3] multimodal dataset consists of eight categories. Such variation exists between text and images because some information can easily be presented in one modality than another modality. For example, it is possible to report missing or found people in text than in an image, which is also reported in [3]. This research focuses on these factors and considers the four most important categories that are useful for crisis responders such as (i) affected, injured, or dead people, (ii) infrastructure and utility damage, (iii) rescue volunteering or donation effort, and (iv) not humanitarian.

**Damage severity**

Detecting the severity of the damage is significantly important to help the affected community during disaster events. The severity of the damage can be assessed from an image based on the visual appearance of the physical destruction of a built structure (e.g., bridges, roads, buildings, burned houses, and forests). In-line with [2], this research defines the following categories for the classification task: (i) severe damage, (ii) mild damage, and (iii) little or none.

### 3.2 Annotations

#### 3.2.1 Data curation

This research extends the labels of the Crisis Benchmark dataset [5]. The Crisis Benchmark dataset was developed by consolidating existing datasets and labeling new data for disaster types. The Crisis Benchmark dataset consists of images collected from Twitter, Google, Bing, Flickr, and Instagram. The majority of the datasets have been collected from Twitter, as shown in Table 2. The Twitter data were mainly collected during major disaster events⁶ and using different disaster-specific keywords. The data collected from Google, Bing, Flickr, and Instagram are based on specific keywords. The dataset is diverse in terms of (i) number of events, (ii) different time frames spanning over five years, (iii) natural (e.g., earthquake, fire, floods) and man-made disasters (e.g., Paris attack, Syria attacks), and (iv) events occurred in different parts of the world. The number of images in different events resulted from different factors, such as the number of tweets collected during the disaster events, the number of images crawled, filtered due to duplicates, and a random selection for the annotation. Our motivation for choosing and extending the Crisis Benchmark dataset is that it reduced the overall cost of data collection and annotation processes while also having a large dataset for MTL.

#### 3.2.2 Multiclass annotation

For the manual annotation, we used Appen⁷ crowdsourcing annotation platform. In such a platform, finding qualified workers and managing the quality of the annotation is an important issue. To ensure the quality, we used the widely used gold standard evaluation approach [84]. We designed the interface with annotation guidelines on Appen for the annotation task (see Fig. 7 in Appendix). We followed the

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⁶ Event names reported in Table 2 are based on Wikipedia.

⁷ https://appen.com/.
annotation guidelines from previous work [3, 5] and improved with examples for this task (see the detailed annotation guidelines with examples in Appendix A).

For all tasks, we first annotated images with a multiclass setting. Then for humanitarian and disaster type tasks we labeled the images with multiple labels as they are more suitable to be framed as pure multilabel setting (see Sect. 3.2.4). For the multiclass labeling, our decision has been influenced by several factors. The most important one was our consultation with humanitarian organizations which suggested limiting the number of classes by merging related ones and keeping only the most important information types. This is due to the information overload issue that humanitarian responders often deal with at the onset of a disaster situation if exposed to information types not important for them. For an image that can have multiple labels, we instructed the annotators to select the label that is more important for humanitarian organizations and prominent in the image.

For the annotation, we designed a HIT containing five images. For the gold standard evaluation, we manually labeled 100 images, which are randomly assigned to the HIT for the evaluation. We assigned a criterion to have at least three annotations per image and per task. An agreement score of 66% is used to select the final label, which ensured that at least two annotators agreed on a label. The HIT was extended to more annotators if such a criterion was not met.

Since the Crisis Benchmark dataset did have taskspecific labels for all images, i.e., different sets of images consisted of labels for three tasks and two tasks, we first prepared different sets with missing labels for the annotation. For example, 25,731 images of the Crisis Benchmark dataset did not have labels for disaster types and humanitarian tasks, which we selected for the annotation tasks. In this way, we run the annotation tasks in different batches.

### 3.2.3 Crowdsourcing results

To measure the quality of the annotation, we compute the annotation agreement using Fleiss kappa [85], Krippendorff’s alpha [86] and average observed agreement [85]. In Table 3, we present the annotation agreement for all events with different approaches mentioned above. The agreement score varies from 46 to 71% for different tasks. Note that, in the Kappa measurement, the values of ranges 0.41–0.60, 0.61–0.80, and 0.81–1 refers to moderate, substantial, and perfect agreement, respectively [87]. Based on these measurements, we conclude that our annotation agreement score leads to moderate to substantial agreement. The number of labels and subjectivity of the annotation tasks reflected the annotation agreement score. Some annotation tasks are highly subjective. For example, for the disaster-type task, hurricane or tropical cyclones often leads to heavy rain, which causes flood (e.g., an image showing a fallen tree with flood water) can be annotated as hurricane or flood. Another example is an image showing building damage and rescue effort. In such cases, the annotation task was to carefully check what is more visible in the image and select the label accordingly. Note that the agreement score for disaster types is comparatively lower than other tasks, which is due to the high level of subjectivity in the annotation task. Annotators needed to choose one label among seven labels. The average agreement scores are comparatively higher as we made sure at least two annotators agree on a label.

#### 3.2.4 Multilabel annotation

For the multilabel annotation for disaster types and humanitarian tasks, we followed a weak supervision approach to assign multiple labels due to the annotation budget (e.g., time, cost). We selected and assigned a set of labels from all annotators. Given that we have three annotators $A_1$, $A_2$, and $A_3$, who assigned a label $l$ from $L = \{l_1, l_2, ..., l_n\}$ to an image $I$, the final label set for the image $I$ is defined as $\bar{l}_I = \{l_1, l'_1, l'_2\}$. Here, the label with majority agreement ($\geq 66\%$) is the same label as in our multiclass setting, and the rest of the labels can have a lower agreement. Note that we were able to assign multiple labels on 53,683 images (75.4%) for disaster types and 65,038 (91.3%) for humanitarian tasks out of 71,198 images (see Table 5). As images have been labeled in different phases and curated from existing sources, we could not properly manage to have multiple labels for all images.

#### 3.2.5 Resulting dataset

After completing the annotation task, the proposed dataset added 155,899 labels for four tasks in addition to the existing 128,893 labels from 71,198 images. In total, this research re-annotated 65,640 images to create the MEDIC dataset. Furthermore, we enriched the MEDIC dataset by separately providing multilabel annotations for disaster types and humanitarian tasks. The distributions for

| Table 3 | Annotation agreement for different tasks |
|---------|-----------------------------------------|
| Tasks       | Fleiss ($\kappa$) | Krip. ($\alpha$) | Avg agg. |
| Disaster types | 0.46 | 0.46 | 0.70 |
| Informativeness | 0.71 | 0.71 | 0.91 |
| Humanitarian | 0.52 | 0.52 | 0.73 |
| Damage severity | 0.55 | 0.55 | 0.79 |

Fleiss Kappa ($\kappa$), Krip. ($\alpha$): Krippendorff’s $\alpha$, Avg agg.: Average observed agreement.
multiclass and multilabel annotations are shown in Tables 4 and 5, respectively. We have analyzed the dataset to understand how tasks and the labels are associated with each other, for which we have computed confusion matrices between pairs of tasks. We find a good correlation between labels across tasks. For example, between humanitarian and damage severity tasks, majority of the not-humanitarian images are also labeled as little or none as shown in Fig. 8d in Appendix A.5. We have similar observations for other task pairs as well. As for the multilabel annotation, majority of the images are labeled with single label. For example, disaster types 84.7% images are labeled with single label and 15.3% with 2-3 labels. For humanitarian, 88.3% are with single label and rest are 11.7%.

### 3.3 Comparison with other datasets

A comparative analysis with prior disaster-related datasets suggests that the MEDIC dataset is larger in size, covering aligned labels for four tasks, and containing multilabel annotations. In Table 6, we present a comparison of the datasets containing aligned labels for MTL. From the table, it is clear that the prior datasets are not designed for this kind of learning setup and the distribution of the class labels is highly skewed (see Table 9 in [88] for Crisis Benchmark Dataset).

| Label                               | Train | Dev  | Test | Total |
|-------------------------------------|-------|------|------|-------|
| **Disaster Types**                  |       |      |      |       |
| Earthquake                          | 12,296| 1004 | 1795 | 15,095|
| Fire                                | 1796  | 262  | 690  | 2748  |
| Flood                               | 3401  | 587  | 1315 | 5303  |
| Hurricane                           | 4517  | 651  | 1518 | 6686  |
| Landslide                           | 1065  | 168  | 331  | 1564  |
| Not disaster                        | 24,459| 3141 | 8885 | 36,485|
| Other disaster                      | 1819  | 344  | 1154 | 3317  |
| **Total**                           | 49,353| 6157 | 15,688| 71,198|
| **Informativeness**                 |       |      |      |       |
| Informative                         | 28,073| 3478 | 7206 | 38,757|
| Not informative                     | 21,280| 2679 | 8,482| 32,441|
| **Total**                           | 49,353| 6157 | 15,688| 71,198|
| **Humanitarian**                    |       |      |      |       |
| Affected injured or dead people     | 3662  | 274  | 639  | 4575  |
| Infrastructure and utility damage   | 18,994| 2440 | 5224 | 26,658|
| Not humanitarian                    | 24,427| 3099 | 9145 | 36,671|
| Rescue volunteering or donation effort | 2270   | 344  | 680  | 3294  |
| **Total**                           | 49,353| 6157 | 15,688| 71,198|
| **Damage Severity**                 |       |      |      |       |
| Little or none                      | 28,314| 3613 | 10,252| 42,179|
| Mild                                | 3904  | 698  | 1527 | 6129  |
| Severe                              | 17,135| 1846 | 3909 | 22,890|
| **Total**                           | 49,353| 6157 | 15,688| 71,198|

| Disaster Types | Train | Dev  | Test | Total |
|----------------|-------|------|------|-------|
| # Labels       |       |      |      |       |
| 1              | 32,227| 3610 | 9635 | 45,472|
| 2              | 5553  | 662  | 1202 | 7417  |
| 3              | 579   | 88   | 133  | 800   |
| **Total**      | 38,359| 4360 | 10,970| 53,689|

| Humanitarian  | Train | Dev  | Test | Total |
|---------------|-------|------|------|-------|
| # Labels      |       |      |      |       |
| 1             | 40,885| 4777 | 11,749| 57,411|
| 2             | 5550  | 491  | 1019 | 7060  |
| 3             | 445   | 37   | 85   | 567   |
| **Total**     | 46,880| 5305 | 12,853| 65,038|

| Table 4 | Annotated dataset with data splits for different tasks |
|---------|------------------------------------------------------|
| Label   | Train | Dev  | Test | Total |
| Disaster Types |       |      |      |       |
| Earthquake | 12,296| 1004 | 1795 | 15,095|
| Fire | 1796  | 262  | 690  | 2748  |
| Flood | 3401  | 587  | 1315 | 5303  |
| Hurricane | 4517  | 651  | 1518 | 6686  |
| Landslide | 1065  | 168  | 331  | 1564  |
| Not disaster | 24,459| 3141 | 8885 | 36,485|
| Other disaster | 1819  | 344  | 1154 | 3317  |
| **Total** | 49,353| 6157 | 15,688| 71,198|

| Humanitarian | Train | Dev  | Test | Total |
|--------------|-------|------|------|-------|
| Affected injured or dead people | 3662 | 274 | 639 | 4575 |
| Infrastructure and utility damage | 18,994| 2440 | 5224 | 26,658|
| Not humanitarian | 24,427| 3099 | 9145 | 36,671|
| Rescue volunteering or donation effort | 2270 | 344 | 680 | 3294 |
| **Total** | 49,353| 6157 | 15,688| 71,198|

| Table 5 | Multilabel annotated dataset with data splits for different tasks |
|---------|------------------------------------------------------|
| Disaster Types | # Labels | Train | Dev  | Test | Total |
| 1 | 32,227 | 3610 | 9635 | 45,472 |
| 2 | 5553  | 662  | 1202 | 7417  |
| 3 | 579   | 88   | 133  | 800   |
| **Total** | 38,359| 4360 | 10,970| 53,689|

| Humanitarian | # Labels | Train | Dev  | Test | Total |
|--------------|----------|-------|------|------|-------|
| 1            | 40,885   | 4777  | 11,749| 57,411|
| 2            | 5550     | 491   | 1019 | 7060  |
| 3            | 445      | 37    | 85   | 567   |
| **Total**    | 46,880   | 5305  | 12,853| 65,038|
4 Experiments and results

In Table 4, we present the dataset with task-wise data splits and distribution for multiclass setting. The distribution for multiclass setting consists of 69%, 9%, and 22% for training, development, and test sets, respectively. We first conduct a baseline experiment, followed by a single-task learning experiment to compare and provide a benchmark for a multi-task setting.

To measure the performance of each classifier and for each task setting, we use weighted average precision (P), recall (R), and F1-score (F1), which are widely used in the literature. For the multilabel experiments we computed micro average precision (P), recall (R), F1-score (F1) and humming loss, which are commonly used metrics [89, 90].

4.1 Baseline

For the baseline experiment we evaluate (i) a majority class baseline, and (ii) fixed features from a pre-trained model used for training and testing SVM and KNN. We extracted features from the penultimate layer of the EfficientNet (b1) model [91], which is trained using ImageNet. The majority class baseline predicts the label based on the most frequent label in the training set. This has been most commonly used in shared tasks [92]. For training SVM and KNN we used standard parameter settings available in sci-kit learn [93].

4.2 Single-task learning

We used several pre-trained models for single-task learning and fine-tuned the network with the task-specific classification layer on top of the network. This approach has been popular and has been performing well for various downstream visual recognition tasks [94–97]. The network architectures that we used in this study include ResNet18, ResNet50, ResNet101 [9], VGG16 [98], DenseNet [99], SqueezeNet [100], MobileNet [101], and EfficientNet [91]. We have chosen such diverse architectures to understand their relative performance and inference time. For fine-tuning, we use the weights of the networks pre-trained using ImageNet [102] to initialize our model. Our classification settings comprised binary (i.e., informativeness task) and multiclass settings (i.e., remaining three tasks). We train the models using the Adam optimizer [103] with an initial learning rate of $10^{-3}$, which is decreased by a factor of 10 when accuracy on the dev set stops improving for 10 epochs. The models were trained for 150 epochs. We use the model with the best accuracy on the validation set to evaluate its performance on the test set.

4.3 Multi-task learning

In the MEDIC dataset, the tasks share similar properties; hence, we designed a simpler approach. We use the hard parameter sharing approach to reduce the computational complexity. All tasks share the same feature layers in the network, which is followed by task-specific classification layers. For optimizing the loss, we provide equal weight to each task. Assuming that the task-specific weight is $w_i$ and task-specific loss function is $L_i$, the optimization objective of the MTL is defined as $L_{MTL} = \sum_i w_i L_i$. During optimization (i.e., using stochastic gradient descent to minimize the objective), the network weights in the shared layers $W_{sh}$ are updated using the following equation:

$$W_{sh} = \sum_i W_{sh} - \frac{\partial L}{\partial W_{sh}}$$

We set $w_i = 1$ in our experiments for all task-specific weights, i.e., equal weight for all tasks. We use softmax activation to get probability distribution over individual tasks and use cross-entropy as a loss function. We initialized the weights using pre-trained models mentioned above, which are trained using ImageNet. Our implementation of multi-task learning supports all the network architectures mentioned in Sect. 4.2. Therefore, we have run experiments using the same pre-trained models and same hyper-parameter settings for the MTL experiments. We used the NVIDIA Tesla V100-SXM2-16 GB GPU machines consisting of 12 cores and 40GB CPU memory for all experiments.

4.4 Multilabel classification

In Table 5, we report the distribution of multilabel data split. It shows that a major part of the dataset is labeled with a single label for both tasks. For the multilabel classification, we run experiments in a single task learning
setup using the models mentioned above. We used the same training environment as other settings discussed in previous sections. However, we used sigmoid activation for multilabel instead of softmax, which is commonly used for multilabel setup.

### 4.5 Results

#### 4.5.1 Baseline

In Table 7, we provide baseline results. From the majority baseline results it is clear that imbalance distribution does not play any role. Among SVM and KNN, the former is performing better in all tasks with 0.2 to 3.3% improvement.

#### 4.5.2 Single- versus multi-task results

In Table 8, we report the results for both single- and multi-task settings using the mentioned models. Across different models, overall, EfficientNet (b1) performs better than other models. Comparing only EfficientNet (b1) results for all tasks, the multi-task setting shows better than single-task settings; although, the difference is minor and might

| Table 7 Baseline classification results |
|----------------------------------------|
| Model                                  | Acc | P   | R   | F1  | Acc | P   | R   | F1  |
|----------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Disaster Types                         |     |     |     |     |     |     |     |     |
| Majority                               | 56.6| 32.1| 56.6| 41.0| 45.9| 21.1| 45.9| 28.9|
| Eff. Net Feat. + KNN                   | 71.1| 72.2| 71.1| 70.1| 80.4| 80.3| 80.4| 80.3|
| Eff. Net Feat. + SVM                   | 75.7| 74.1| 75.7| 73.2| 83.0| 83.0| 83.0| 83.0|
| Infominerial                            |     |     |     |     |     |     |     |     |
| Majority                               | 58.3| 34.0| 58.3| 42.9| 65.3| 42.7| 65.3| 51.7|
| Eff. Net Feat. + KNN                   | 75.3| 74.8| 75.3| 74.6| 76.5| 73.9| 76.5| 74.8|
| Eff. Net Feat. + SVM                   | 77.9| 76.1| 77.9| 76.1| 78.3| 75.1| 78.3| 75.1|

Eff. Net Feat.: Feature extracted from the penultimate layer of a pre-trained efficient net model

Best F1 results are highlighted in bold

| Table 8 Classification results using single and multi-task settings along with different pre-trained models |
|---------------------------------------------------------------|
| Model                              | Acc Single-task | P | R | F1 | Acc Multi-task | P | R | F1 |
|------------------------------------|----------------|---|---|----|----------------|---|---|----|
| Disaster Types                     |                |   |   |    |                |   |   |    |
| ResNet18                           | 79.8           | 78.3| 79.8| 79.1| 79.8| 77.9| 82.6| 81.6| 82.6| 81.9| 83.2| 82.0| 83.2| 82.2|
| ResNet50                           | 80.6           | 79.7| 80.6| 80.9| 80.9| 79.4| 83.4| 83.1| 83.4| 83.0| 84.2| 83.5| 84.2| 83.7|
| ResNet101                          | 81.3           | 80.4| 81.3| 81.1| 81.0| 78.9| 83.9| 83.1| 83.9| 83.4| 84.6| 83.7| 84.6| 83.9|
| VGG16                              | 80.0           | 78.5| 80.0| 80.7| 80.7| 78.7| 83.6| 82.7| 83.6| 83.0| 84.1| 83.1| 84.1| 83.4|
| DenseNet (121)                     | 81.1           | 80.2| 81.1| 79.5| 80.2| 80.7| 78.8| 83.4| 82.5| 83.4| 82.7| 83.9| 83.0| 83.9| 83.2|
| SqueezeNet                         | 76.5           | 75.0| 76.5| 75.5| 75.1| 74.7| 79.8| 78.0| 79.8| 78.4| 81.0| 79.5| 81.0| 79.9|
| MobileNet (v2)                     | 80.1           | 79.0| 80.1| 78.0| 79.2| 79.9| 82.7| 82.7| 82.7| 82.0| 83.5| 82.5| 83.5| 82.7|
| EfficientNet (b1)                  | 82.1           | 81.6| 82.1| 80.7| 81.4| 81.1| 79.8| 84.3| 83.9| 84.3| **84.0**| 84.6| 84.2| 84.6| **84.3**|
| EfficientNet (b7)                  | 81.0           | 79.9| 81.0| 79.1| 80.5| 79.5| 80.5| 80.7| 83.2| 82.4| 83.2| 82.7| 83.2| 82.4| 83.2|
| Humanitarian                       |                |   |   |    |                |   |   |    |
| Disaster Types                     |                |   |   |    |                |   |   |    |
| ResNet18                           | 85.9           | 86.2| 85.9| 86.8| 86.9| 86.8| 86.8| 81.4| 78.4| 81.4| 79.1| 81.7| 81.7| 81.7| 79.3|
| ResNet50                           | 87.4           | 87.4| 87.4| 87.8| 88.0| 87.8| 82.1| 79.2| 82.1| 79.9| 82.8| 80.3| 82.8| 80.7|
| ResNet101                          | 87.4           | 87.6| 87.4| 88.3| 88.3| 88.3| 88.3| 82.3| 79.9| 82.3| **80.6**| 82.9| 79.9| 82.9| 80.2|
| VGG16                              | 86.7           | 87.1| 86.7| 86.8| 87.6| 87.7| 87.6| 86.2| 79.6| 82.3| 79.7| 82.7| 80.1| 82.7| 80.5|
| DenseNet (121)                     | 87.1           | 87.2| 87.1| 87.5| 87.6| 87.5| 87.5| 82.4| 80.0| 82.4| 80.4| 82.5| 79.6| 82.5| 80.3|
| SqueezeNet                         | 83.9           | 84.2| 83.9| 85.0| 85.1| 85.0| 59.7| 76.5| 79.7| 80.5| 76.7| 80.5| 76.7| 80.5| 77.5|
| MobileNet (v2)                     | 86.2           | 86.4| 86.2| 86.3| 86.7| 87.0| 86.7| 86.8| 81.7| 81.7| 78.9| 82.1| 79.3| 82.1| 79.7|
| EfficientNet (b1)                  | 87.7           | 87.7| 87.7| 87.7| 88.6| 88.7| 88.6| **86.6**| 82.8| 82.8| 82.4| 80.7| 82.9| 80.7| **80.8**|
| EfficientNet (b7)                  | 87.2           | 87.2| 87.2| 87.2| 87.5| 87.6| 87.5| 87.5| 81.9| 81.9| 80.0| 82.0| 79.5| 82.0| 80.3|

Best F1 result for each task setting is highlighted in bold
not be significant. However, since we share the feature layers across the four tasks, model space requirement and inference time are reduced by a factor of four. The improved inference time is crucial for real-time disaster response systems as it reduces the operational cost that running individual models would incur.

### 4.5.3 Multi-task results using different random seeds

In our experiment, only the weights of the last layer were initialized randomly, hence, this can result in a minor variation in the performance. We have run experiments using different random seeds with the MTL setting. In Table 9, we report results on selected models for all tasks. We observe that variation is very minor and among different models, DenseNet (121) shows relatively lower variation across tasks.

### 4.5.4 Ablation experiments in multi-task setup

To understand the task correlation and how they affect performance, we also run experiments with different subsets of the tasks (see Table 10). We obtain similar results with other task combinations. In Table 10, we show results obtained using combination of different subset of tasks. We observe that the results remain consistent with other combinations of tasks as well. It will be an important future research avenue to explore different weighting schemes for the tasks. Regardless, our reported results can serve as a baseline for single and multi-task disaster image classification.

### 4.5.5 Multilabel classification results

In Table 11, we report multilabel classification results for disaster types and humanitarian tasks. Overall, across

| Model | DT | Info | Hum | DS |
|-------|----|------|-----|----|
| ResNet101 | 79.4 ± 0.1 | 86.2 ± 0.1 | 80.7 ± 0.1 | 80.5 ± 0.1 |
| VGG16       | 79.3 ± 0.4 | 86.2 ± 0.1 | 80.6 ± 0.1 | 80.3 ± 0.2 |
| DenseNet (121) | 79.2 ± 0.1 | **86.2 ± 0.04** | **80.7 ± 0.03** | 80.4 ± 0.1 |
| EfficientNet (b1) | **79.5 ± 0.4** | 88.5 ± 0.3 | 84.2 ± 0.1 | **80.6 ± 0.3** |

| Model (task setup) | DT | Info | Hum | DS |
|-------------------|----|------|-----|----|
| DT-Info-Hum-Ds     | 79.8 | 88.6 | 84.3 | 80.8 |
| DT-Info-Hum       | 80.3 | **88.9** | **84.5** | 80.7 |
| DT-Info-Ds        | 80.2 | 88.6 | **81.0** | Info-Hum |
| DT-Info          | 80.1 | 88.7 | 84.2 | 80.5 |
| DT-Hum          | **80.5** | 84.4 | Hum-DS | 84.1 |

**Table 10** Results (F1) with different combination of tasks using Efficient-Net (b1)

| Model (task setup) | DT | Info | Hum | DS |
|-------------------|----|------|-----|----|
| DT-Info-Hum-Ds     | 79.8 | 88.6 | 84.3 | 80.8 |
| DT-Info-Hum       | 80.3 | **88.9** | **84.5** | 80.7 |
| DT-Info-Ds        | 80.2 | 88.6 | **81.0** | Info-Hum |
| DT-Info          | 80.1 | 88.7 | 84.2 | 80.5 |
| DT-Hum          | **80.5** | 84.4 | Hum-DS | 84.1 |

**Table 11** Classification results using single-task multilabel settings with different pre-trained models

| Model | Acc Disaster Type | P R F1 H | Acc Humanitarian | P R F1 H |
|-------|------------------|---------|------------------|---------|
| ResNet18 | 73.9 | 86.2 | 73.2 | 79.2 | 6.2 | 76.5 | 85.4 | 78.4 | 81.8 | 9.6 |
| ResNet50 | 76.3 | 86.1 | 75.6 | 80.5 | 5.9 | 78.6 | 86.4 | 80.5 | 83.3 | 8.8 |
| ResNet101 | 75.8 | 86.2 | 75.9 | 80.7 | 5.9 | 79.0 | 86.6 | 80.4 | **83.4** | 8.8 |
| VGG16       | 76.2 | 86.8 | 75.6 | **80.8** | 5.8 | 78.9 | 86.3 | 80.5 | 83.3 | 8.8 |
| DenseNet (121) | 75.8 | 87.6 | 74.3 | 80.4 | 5.9 | 78.0 | 86.5 | 78.9 | 82.5 | 9.1 |
| SqueezeNet  | 36.3 | 41.8 | 64.3 | 50.7 | 20.3 | 31.9 | 55.3 | 78.9 | 65.0 | 23.2 |
| MobileNet (v2) | 73.5 | 86.4 | 71.8 | 78.4 | 6.4 | 76.8 | 86.0 | 78.0 | 81.8 | 9.5 |
| EfficientNet (b1) | 73.4 | 86.1 | 71.5 | 78.1 | 6.5 | 77.9 | 86.1 | 79.9 | 82.9 | 9.0 |
| EfficientNet (b7) | 76.0 | 86.0 | 74.7 | 80.0 | 6.1 | 78.2 | 85.4 | 80.3 | 82.8 | 9.1 |

_H: Humming Loss_ lower is better. Micro average precision, recall, and F1

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different models, SqueezeNet is the worst performing model, which we also observed for single and multi-task multiclass classification results. The multilabel results, as in Table 10, are not equally comparable with multiclass results, as reported in Table 8. This results will serve as baselines in future studies.

4.5.6 Error analysis

Given that class distribution can play a significant role in classifier performance, we explored whether low prevalent classes have any significant impact. In Table 12, we report task-wise classification results for both single and multi-task settings in which the model is trained using EfficientNet model. It appears that low prevalent classes have lower performance. However, this is not always the case. For example, the distribution of Fire class label is 3.8% in the dataset but the performance is third-best among class labels. Where the distribution of Other disaster is 5.1%, however, the F1 is 27.0, which is the lowest performance. With our analysis, we found that this Other disaster confused with Not disaster (see Table 14 in Appendix B).

In Tables 14, 15, 16 and 17 (in Appendix B) we report classification confusion matrices using EfficientNet (b1) model for disaster types, informative, humanitarian and damage severity, respectively. From the tables, we observe that there is comparable performances between different task settings. In some cases class label performance increases in multi-task setting and in some cases it decreases. For example, true positives increase for informative and decreases for not-informative in multi-task setting. The results in these tables also confirm the results in Table 8.

4.5.7 Computational time analysis

We have done extensive analysis to understand whether multi-task learning setup reduces computational time. In Table 13, we provide such findings for all the models we used in our experiments. From the results, it is clear that multi-task learning setup can significantly reduce the computation time both in terms of training and inference.

5 Discussion and future work

The MEDIC dataset provides images from diverse events consisting of different time frames. The crowdsourced annotation provides a reasonable annotator agreement even though the task is subjective. Our experiments show that multi-task learning with neural networks reduces

| Table 12 | Class-wise results for both single and multi-task settings using EfficientNet (b1) model |
|----------|--------------------------------------------------|
| Label                | P Single-task | R | F1 | P Multi-task | R | F1 |
|----------------------|--------------|---|----|--------------|---|----|
| Disaster Type        |              |   |    |              |   |    |
| Earthquake           | 73.8         | 82.6 | 77.9 | 70.5         | 83.5 | 76.4 |
| Fire                 | 78.2         | 85.2 | 81.6 | 74.1         | 85.4 | 79.3 |
| Flood                | 78.1         | 80.7 | 79.4 | 78.5         | 80.8 | 79.6 |
| Hurricane            | 65.6         | 67.5 | 66.6 | 64.4         | 63.0 | 63.7 |
| Landslide            | 62.2         | 78.5 | 69.4 | 60.4         | 75.5 | 67.1 |
| Not disaster         | 88.9         | 92.9 | 92.7 | 88.9         | 92.7 | 90.8 |
| Other disaster       | 70.5         | 18.8 | 29.7 | 72.6         | 15.6 | 25.7 |
| Informativeness      |              |   |    |              |   |    |
| Informative          | 86.5         | 86.8 | 86.7 | 85.8         | 90.0 | 87.9 |
| Not-informative      | 88.8         | 88.5 | 88.6 | 91.2         | 87.3 | 89.2 |
| Humanitarian         |              |   |    |              |   |    |
| Affected, injured, or dead people | 54.8 | 42.6 | 47.9 | 51.5 | 43.8 | 47.3 |
| Infrastructure and utility damage | 81.5 | 85.1 | 83.2 | 80.6 | 87.8 | 84.1 |
| Not humanitarian     | 89.8         | 89.9 | 89.9 | 91.1         | 89.2 | 90.1 |
| Rescue volunteering or donation effort | 48.7 | 42.2 | 45.2 | 49.4 | 36.2 | 41.8 |
| Damage Severity      |              |   |    |              |   |    |
| Little or none       | 89.7         | 93.2 | 91.4 | 91.0         | 92.4 | 91.7 |
| Mild                 | 42.3         | 9.8  | 15.9 | 40.7         | 11.7 | 18.2 |
| Severe               | 70.2         | 84.3 | 76.6 | 69.2         | 85.6 | 76.5 |
computational complexity significantly while having comparative performance.

In Fig. 2, we show the loss and accuracy plots for single and multi-task settings for EfficientNet (b1) model. We limit the plots to 40 epochs as all of the models converged by then. We notice similar convergence rates for both single and multi-task learning setups. We observe that the multi-task objective function acts as a regularizer as the training loss is consistently higher and training accuracy is lower than the single-task setting while having similar or better performance on the validation set. This suggests that the multi-task setup may benefit from models having a larger capacity.

Class distribution is an important issue that affect classifier performance. We investigated class-wise performances and confusion matrix. Our observation suggests that imbalanced class distribution is not only factor for lower classification performance in certain classes. It also depends on distinguishing properties of the class label. For example, the distribution of Fire class label is 3.8% in the dataset but the performance is third-best among class labels. Where the distribution of Other disaster is 5.1%, however, the F1 is 27.0, which is the lowest performance.

**Future work**

Our future work includes exploring other multi-task learning methods, and investigating tasks groups and relationships. For instance, further investigation is needed to explain why training the model with disaster types, informativeness and humanitarian tasks reduces performance as presented in Table 10. Other research avenues include multimodality (e.g., integrating text), and investigating class imbalance issues.

## 6 Conclusions

We presented a large-scale, manually annotated multi-task learning dataset, comprising 71,198 images labeled for four tasks, which were specifically designed for multi-task learning research and disaster response image classification. The dataset will not only be useful to develop robust models for disaster response tasks but will also enable evaluation of general multi-task models. We provide classification results using nine different pre-trained models, which can serve as a benchmark for future work. We report that the multi-task model reduces the inference time significantly, hence, such a model can be very useful for real-time classification tasks, especially for analyzing social media image streams.
Appendix

Appendix A Data collection

A.1 Data curation and annotation

We extended the Crisis Benchmark dataset to develop MEDIC, a multi-task learning dataset for disaster response. For the annotation, we provided detailed instructions to the annotators, which they followed during the annotation tasks. Our annotation consists of four tasks in different batches, and we provided task-specific instructions along with them.

A.2 Annotation instructions

The annotation task involves identifying images that are useful for humanitarian aid/response. During different disaster events (i.e., natural and human-induced or hybrid), humanitarian aid involves assisting people who need help. The primary purpose of humanitarian aid is to save lives, reduce suffering, and rebuild affected communities. Among the people in need belong homeless, refugees, and victims of natural disasters, wars, and conflicts who need necessities like food, water, shelter, medical assistance, and damage-free critical infrastructure and utilities such as roads, bridges, power lines, and communication poles.

For disaster types and humanitarian tasks, it is possible that some images can be annotated with multiple labels. In such cases, the instruction is to choose a label that is critical (i.e., higher priority) for humanitarian organizations and more prominent in the image.

A.2.1 Disaster types

The purpose of identifying disaster type is to understand the type of disaster events shared in an image. The annotation task involves looking into the image can carefully select one of the following disaster types based on their specific definition. There might be the case that an image shows an effect of a hurricane (destroyed house) and also flood, in such cases the task is to carefully check what is more visible and select label accordingly. Example of images demonstrating different disaster types is shown in Fig. 3.

- Earthquake: this type of images shows damaged or destroyed buildings, fractured houses, ground ruptures such as railway lines, roads, airport runways, highways, bridges, and tunnels.
- Fire: image shows man-made fires or wildfires (forests, grasslands, brush, and deserts), destroyed forests, houses, or infrastructures.
- Flood: image shows flooded areas, houses, roads, and other infrastructures.
- Hurricane: image shows high winds, a storm surge, heavy rains, collapsed electricity polls, grids, and trees.

Fig. 2 Training and validation loss and accuracy for EfficientNet (b1) model for single and multi-task settings
Landslide: image shows landslide, mudslide, landslip, rockfall, rockslide, earth slip, and land collapse

Other disasters: image shows any other disaster types such as plane crash, bus, car, or train accident, explosion, war, and conflicts.

Not disaster: image shows cartoon, advertisement, or anything that cannot be easily linked to any disaster type.

A.2.2 Informativeness

The purpose of this task is to determine whether image is useful for humanitarian aid purposes as defined below. If the given image is useful for humanitarian aid, the annotation task is to select the label “Informative”, otherwise select the label “Not informative” image. Example of images demonstrating informative versus not-informative is shown in Figs. 3, 4.

- Informative: if an image is useful for humanitarian aid and shows one or more of the following: cautions, advice, and warnings, injured, dead, or affected people, rescue, volunteering, or donation request or effort, damaged houses, damaged roads, damaged buildings; flooded houses, flooded streets; blocked roads, blocked bridges, blocked pathways; any built structure affected by earthquake, fire, heavy rain, strong winds, gust, etc., disaster area maps.

- Not informative: if the image is not useful for humanitarian aid and shows advertising, banners, logos, cartoons, and blurred.

A.2.3 Humanitarian categories

Based on the humanitarian aid definition above, we define each humanitarian information category below. Example images are shown in Fig. 5.

- Affected, injured or dead people: image shows injured, dead, or affected people such as people in shelter facilities, sitting or lying outside, etc.

- Infrastructure and utility damage: image shows any built structure affected or damaged by the disaster. This includes damaged houses, roads, buildings; flooded houses, streets, highways; blocked roads, bridges,
pathways; collapsed bridges, power lines, communication poles, etc.

- **Not humanitarian**: image is not relevant or useful for humanitarian aid and response such as non-disaster scenes, cartoons, advertisement banners, celebrities, etc.

- **Rescue, volunteering, or donation effort**: image shows any type of rescue, volunteering, or response effort such as people being transported to safe places, people being evacuated from the hazardous area, people receiving medical aid or food, donation of money, blood, or services, etc.

### A.2.4 Damage Severity

The purpose of this task is to identify the severity of damage reported in an image (Fig. 6). It can be physical destruction to a build-structure. Our goal is to detect physical damages like broken bridges, collapsed or shattered buildings, destroyed or creaked roads. We define each damage severity category below.

1. **Severe**: Substantial destruction of an infrastructure belongs to the severe damage category. For example, a non-livable or non-usable building, a non-crossable bridge, or a non-drivable road, destroyed, burned crops, forests are all examples of severely damaged infrastructures. For example, if one or more building in the image show substantial loss of amenity or images shows a building that is not safe to use then such image should be labeled as severe damage.

2. **Mild**: Partially destroyed buildings, bridges, houses, roads belong to mild damage category. For example, if image shows a building with damage up to 50%, partial loss of amenity/roof or part of the building can has to be closed down then it should label as mild damage.

3. **Little or none**: Images that show damage-free infrastructure (except for wear and tear due to age or disrepair) belong to the little-or-no-damage category.

### A.3 Annotation interface

An example of annotation interface is show in in Fig. 7. Image on the left shows annotation task is launched to annotate image for disaster type and humanitarian tasks and image on the right shows annotation task is launched for three tasks.

### A.4 Manual annotation

In our annotation tasks through the Appen platform, more than 3000 annotators participated from more than 50 countries. For the annotation task, we estimated hourly wages and it was 6 to 8 USD per hour on average, which varied depending on the two to three labels annotation per image. We think such pay is reasonable as annotators are from various part of the world where wages varies depending on the location. In total we paid 5,159 USD for the annotation, including Appen charges.
A.5 Data analysis

In Fig. 8, we report class-wise relationship between tasks. It appears that there is an association between labels for different tasks. For example, for disaster types and informativeness tasks, as shown in the Fig. 8a, not disaster and not informative are highly related. A major part of not disaster images are labeled as little or none damages as shown in 8b. Our observations for other task combinations are quite similar for different label pairs.

Appendix B Error analysis

In Tables 14, 15, 16 and 17, we report confusion matrices for different tasks with a comparison to single vs. multi-task settings.

Model Parameters

In Table 18, we report model parameters and their memory consumption.

Appendix C The MEDIC dataset

The dataset can be downloaded from https://crisnlp.qcri.org/medic/index.html.

C.1 Data format

The dataset format can be found in https://crisnlp.qcri.org/medic/index.html.

C.2 Terms of use, privacy and license

The MEDIC dataset is published under CC BY-NC-SA 4.0 license, which means everyone can use this dataset for non-commercial research purpose: https://creativecommons.org/licenses/by-nc/4.0/.

C.3 Data maintenance

We provide data download link through https://crisnlp.qcri.org/medic/index.html. We also host the dataset on Zenodo\(^8\) for wider access. We will maintain the data for a long period of time and make sure dataset is accessible.

C.4 Benchmark code

The benchmark code is available at: https://github.com/firojalam/medic/.

C.5 Ethics statement

C.5.1 Dataset collection

The dataset contains images from multiple sources such as Twitter, Google, Bing, Flickr, and Instagram. Twitter developer terms and conditions suggests that one can release 50K tweet objects\(^9\) and here we only provide images not whole JSON objects. The total number of images from Twitter is less than 50,000. Hence, by

\(^8\) https://doi.org/10.5281/zenodo.6625120.
\(^9\) http://developer.twitter.com/en/developer-terms/agreement-and-policy.
Fig. 8 Contingency heatmaps for different pairs of tasks

(a) DT and info.

(b) DT and DS.

(c) DS and hum.

(d) Hum and DS.

(e) Info and DS.

(f) Info and hum.
### Table 14: Confusion matrix for disaster types task using single vs. multi-task learning with efficient-net (b1) model

| Label            | Earthquake | Fire | Flood | Hurricane | Landslide | Not disaster | Other disaster | Total  |
|------------------|------------|------|-------|-----------|-----------|--------------|----------------|--------|
| **Single-task**  |            |      |       |           |           |              |                |        |
| Earthquake       | 1482       | 22   | 14    | 66        | 38        | 156          | 17             | 1795   |
| Fire             | 17         | 588  | 3     | 9         | 4         | 66           | 3              | 690    |
| Flood            | 19         | 5    | 1061  | 64        | 20        | 145          | 1              | 1315   |
| Hurricane        | 104        | 10   | 92    | 1025      | 29        | 234          | 24             | 1518   |
| Landslide        | 27         | 3    | 7     | 13        | 260       | 21           | 0              | 331    |
| Not disaster     | 122        | 53   | 142   | 241       | 28        | 8253         | 46             | 8885   |
| Other disaster   | 237        | 71   | 39    | 144       | 39        | 407          | 217            | 1154   |
| **Total**        | 2008       | 752  | 1358  | 1562      | 418       | 9282         | 308            | 15688  |
| **Multi-task**   |            |      |       |           |           |              |                |        |
| Earthquake       | 1498       | 22   | 12    | 69        | 34        | 150          | 10             | 1795   |
| Fire             | 21         | 589  | 3     | 11        | 3         | 60           | 3              | 690    |
| Flood            | 24         | 6    | 1062  | 55        | 20        | 147          | 1              | 1315   |
| Hurricane        | 151        | 16   | 112   | 956       | 41        | 232          | 10             | 1518   |
| Landslide        | 30         | 4    | 5     | 16        | 250       | 26           | 0              | 331    |
| Not disaster     | 130        | 76   | 121   | 243       | 34        | 8237         | 44             | 8885   |
| Other disaster   | 272        | 82   | 38    | 135       | 32        | 415          | 180            | 1154   |
| **Total**        | 2126       | 795  | 1353  | 1485      | 414       | 9267         | 248            | 15688  |

### Table 15: Confusion matrix for informative task using single vs. multi-task learning with efficient-net (b1) model

| Label              | Single-task |          |          |          |          |          |          |          |          |
|--------------------|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
|                    | Informative | Not Informative | Total | Informative | Not Informative | Total |          |          |          |
| **Informative**    | 6256        | 950      | 7206     | 6489      | 717      | 7206     |          |          |          |
| **Not Informative**| 977         | 7505     | 8482     | 1076      | 7406     | 8482     |          |          |          |
| **Total**          | 7233        | 8455     | 15688    | 7565      | 8123     | 15688    |          |          |          |

### Table 16: Confusion matrix for humanitarian task using single vs. multi-task learning with efficient-net (b1) model

| Label                          | Single-task |          |          |          |          |          |          |          |          |
|--------------------------------|-------------|----------|----------|----------|----------|----------|----------|----------|----------|
|                                | Affected    | Infra. damage | Not hum | Rescue   | Total    | Affected    | Infra. damage | Not hum | Rescue   |
| **Affected, injured, or dead people** | 272         | 181      | 149      | 37       | 639      | 280         | 191      | 137      | 31       | 639     |
| Infrastructure and utility damage | 68          | 4445     | 630      | 81       | 5224     | 67          | 4588     | 522      | 47       | 5224    |
| Not humanitarian               | 93          | 649      | 8219     | 184      | 9145     | 118         | 698      | 8155     | 174      | 9145    |
| Rescue volunteering or donation effort | 63          | 180      | 150      | 287      | 680      | 79          | 214      | 141      | 246      | 680     |
| **Total**                      | 496         | 5455     | 9148     | 589      | 15688    | 544         | 5691     | 8955     | 498      | 15688   |
releasing the data by maintaining such terms and conditions. From Google, Bing, Yahoo and Instagram images are publicly available. In addition, we also maintain licenses and cite prior work based upon we built our work.

C.5.2 Potential negative societal impacts

The dataset consists of images collected from social media and different search engines. We have given our best efforts to eliminate any adult content during data preparation and annotation. Hence, we believe that the presence of such content in the dataset might be very unlikely. Our annotation does not contain any identifiable information such as age, gender, or race. However, the images in the dataset have many faces and one might apply facial recognition to identify someone. Intervention with human moderation would be required in order to ensure this does not lead to any misuse. We also would like to highlight that the models’ prediction should be used carefully as the purpose of the models’ prediction is to facilitate its user, not to make any direct decision. Model designers also need to be careful for any adversarial attack that can lead to creation and spread of any mis/disinformation.

C.5.3 Biases

The datasets are not representative of a geolocation, user gender, age, race, so should not be used in analyses requiring a representative sample. Instead, the datasets are more suitable to be combined with existing datasets and used for training supervised machine learning models.

We also would like to highlight that some of the annotations are subjective, and we have clearly indicated in the text which of these are. Thus, it is inevitable that there would be biases in our dataset. Note that, we have very clear annotation instructions with examples in order to reduce such biases.

C.5.4 Intended use

The dataset can enable an analysis of image content for disaster response, which could be of interest to crisis responders humanitarian response organizations, and policymakers. There are only very few datasets available for multi-task learning research. This dataset can significantly help towards this direction. Having a single model for multiple tasks can also foster Green AI.

Funding Open Access funding provided by the Qatar National Library.

Data availability The dataset proposed in this research is available to download from the following links: https://crisisnlp.qcri.org/medic/index.html and https://doi.org/10.5281/zenodo.6625120. More details about the dataset is available in Appendix C.

Declarations

Conflict of interest The authors have no competing interests.

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| Arch       | # Layer | # Param (M) | Memory (MB) |
|------------|---------|-------------|-------------|
| ResNet18   | 18      | 11.18       | 74.61       |
| ResNet50   | 50      | 23.51       | 233.54      |
| ResNet101  | 101     | 42.50       | 377.58      |
| AlexNet    | 8       | 57.01       | 222.24      |
| VGG16      | 16      | 134.28      | 673.87      |
| DenseNet (121) | 121 | 6.96 | 174.2 |
| SqueezeNet | 18      | 0.74        | 47.99       |
| InceptionNet (v3) | 42  | 24.35       | 206.01      |
| MobileNet (v2) | 20 | 2.23        | 8.49        |
| EfficientNet (b1) | 25 | 7.79        | 177.82      |

Table 17 Confusion matrix for damage severity task using single vs. multi-task learning with efficient-net (b1) model

| Label          | Single-task |       |       |       | Multi-task |       |       |       |
|----------------|-------------|-------|-------|-------|------------|-------|-------|-------|
|                | Little or none | Mild | Severe | Total | Little or none | Mild | Severe | Total |
| Little or none | 9550        | 120  | 582   | 10252 | 9476        | 152  | 624   | 10252 |
| Mild           | 563         | 149  | 815   | 1527  | 481         | 179  | 867   | 1527  |
| Severe         | 530         | 83   | 3296  | 3909  | 453         | 109  | 3347  | 3909  |
| Total          | 10643       | 352  | 4693  | 15688 | 10410       | 440  | 4838  | 15688 |

Table 18 Model parameters: number of layer, parameter, and size of the memory consumption
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