The SocialDisNER shared task on detection of disease mentions in health-relevant content from social media: methods, evaluation, guidelines and corpora

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Abstract
There is a pressing need to exploit health-related content from social media, a global source of data where key health information is posted directly by citizens, patients and other healthcare stakeholders. Use cases of disease-related social media mining include disease outbreak/surveillance, mental health and pharmacovigilance. Current efforts address the exploitation of social media beyond English. The SocialDisNER task, organized as part of the SMM4H 2022 initiative (Weissenbacher et al., 2022), has applied the LINKAGE methodology to select and annotate a Gold Standard corpus of 9,500 tweets in Spanish enriched with disease mentions generated by patients and medical professionals. As a complementary resource for teams participating in the SocialDisNER track, we have also created a large-scale corpus of 85,000 tweets, where in addition to disease mentions, other medical entities of relevance (e.g., medications, symptoms and procedures, among others) have been automatically labelled. Using these large-scale datasets, co-mention networks or knowledge graphs were released for each entity pair type. Out of the 47 teams registered for the task, 17 teams uploaded a total of 32 runs. The top-performing team achieved a very competitive 0.891 f-score, with a system trained following a continue pre-training strategy. We anticipate that the corpus and systems resulting from the SocialDisNER track might further foster health-related text mining of social media content in Spanish and inspire disease detection strategies in other languages. Corpus: https://doi.org/10.5281/zenodo.6359365

1 Introduction
With more than 4.2 billion users worldwide, social media have become the most widely used digital platform for interacting with peers as well as accessing information relevant to specific groups (Kemp, 2021). Specifically Twitter, an online micro-blogging social network (OSN), has been widely used to extract information about people: from opinions and effects of environmental pollution (Gasco et al., 2019; Otero et al., 2021) to biomedical aspects such as adverse drug reactions (OConnor et al., 2014; MacKinlay et al., 2017), public health (Collier et al., 2008), and the psychological effects of a pandemic on the population (Aiello et al., 2021).

Most analysis and information extraction studies are carried out in English, the main language used by the platform’s users. However, other major languages such as Spanish have generated a large amount of potentially usable data for analysis (Alshaabi et al., 2021), which increases the impact of NLP systems able to extract information in this language.

To date, the resources for working with Twitter data in Spanish have focused on corpora to extract information related to emotions (Plaza-del Arco et al., 2020; Martinez-Camara et al., 2015) and professions (Miranda-Escalada et al., 2021). Recently, language models trained with Spanish tweets have been developed to improve the performance of NLP tasks applied to data obtained from this OSN (Huertas-Tato et al., 2022). However, there is a clear lack of corpora to train systems capable of extracting biomedical information from Spanish content that could be used for real-time mining of health information posted by patients, which is of growing interest for different scenarios such as screening for rare diseases (Miller et al., 2021).

One of the main entities to effectively recognise health-related content is diseases. Shared-task such as DisTEMIST (Miranda-Escalada et al., 2022; Nentidis et al., 2022), which focused on the detection of disease mentions in clinical cases, fostered the creation of many tools for this purpose. These systems focus on extracting information from technical and scientific texts, but their performance is limited to the more lay language used in social networks. In the SocialDisNER shared task, we have applied the knowledge and experience from clinical cases acquired in DisTEMIST to detect disease mentions in Spanish tweets written by patients and
medical professionals.

2 Task Description

Shared Task Goal. SocialDisNER focuses on the recognition of disease mentions in Twitter posts. Tweets originate from the following: patients’ accounts, with firsthand health reports; friends, support network and relatives, who share the difficulties faced by patients; and medical professionals, who disseminate reliable information about diseases. Tweets in this task include information on rheumatic diseases such as lupus erythematosus, highly prevalent diseases such as cancer, diabetes, obesity and mental disorders, fibromyalgia and autism spectrum conditions.

Shared Task Setting. The track comprised a single challenge in which participants were required to train NLP systems capable of detecting disease mentions automatically. We conducted the task using CodaLab in a three-stage scenario. In the practice phase, the training and evaluation set were released so that participants could build their systems and evaluate their models on the validation set. For the evaluation phase, the test and background set were released without annotations for the participant teams to compute and submit their predictions. Teams were only evaluated on the test set, using the background data to avoid possible manual corrections and to evaluate the scalability of the systems. In this phase, the participants were only allowed to upload 2 runs. In order to further develop disease mention recognition systems in tweets, the competition has been kept open in the post-evaluation phase, so that researchers continue to measure and compare the performance of their systems.

Evaluation metrics. Teams were evaluated and ranked using micro-average F1 score. In addition to this metric, micro-averaged precision and recall were computed. The evaluation script is available on Github1. We also compared the systems versus a baseline model following a lexical search approach (TeMU-BSC, 2022).

3 Corpus and resources

3.1 SocialDisNER Gold Standard

Gold Standard selection methodology. SocialDisNER has compiled a set of 9,500 tweets written in Spanish containing patient and family members experiences about diseases and relevant content written by clinical professionals. The LINKAGE methodology was created to obtain a larger number of tweets posted by patients themselves and relevant professionals. This methodology has been designed to avoid noisy health twitter content and biases associated with keyword-based selection (Kowald and Lex, 2018). The procedure, shown in the Figure 1, consists of 4 stages:

1. Followers Network Creation: First, a user network with a common interest in the health field is downloaded. For SocialDisNER, a total of 993 seed Twitter accounts of patient associations, health professionals and healthcare institutions were selected and manually curated by task organizers. We obtained the followers from this pool of accounts, resulting in a community of 287,417 users.

2. Data Gathering: Second, the content published by this community of users was downloaded using the Twitter API. In the task, only the original tweets written by users were

1https://github.com/TeMU-BSC/socialdisner_evaluation_script
downloaded, ignoring retweets and replies to other tweets. Tweets posted between February 2019 and February 2022 were downloaded to prevent having data only about the COVID-19 pandemic, as we have tweets prior to the beginning of it. After this downloading process, more than 12.7 million tweets were obtained.

3. **Data Preparation**: Third, rules were applied to filter out irrelevant content as follows: a) tweets written in a language other than Spanish according to the Twitter API; b) tweets with less than 7 tokens, as they might not contain substantial information about diseases; and c) documents in which more than 50% of tokens were mentions. A data enrichment process was applied to the resulting set to produce the final candidates. On the one hand, biomedical mentions such as symptoms, procedures, diseases and drugs were extracted using NER systems developed in previous works (Gonzalez-Agirre et al., 2019). Only tweets with at least one disease mention were selected. First-person characteristics, such as the presence of first-person pronouns, were also calculated, considering only tweets that at least had a first-person attribute. After these constraints, a set of more than 240k tweets were obtained.

4. **Data Selection**: Finally, criteria were determined for selecting candidate tweets to be annotated by experts. Selection strategies were applied so that there was content with several mentions of diseases written in the first person and also had mentions of other biomedical diseases such as symptoms, procedures and medications. The selection criteria for the development and test sets were the same. At the end of this phase, 11,500 tweets were selected for annotation.

**Gold Standard statistics.** Tweets were annotated by a medical expert during 3 months using an adaptation of the DisteMIST annotation guidelines, whose agreement was tested among medical and linguistic experts with an IAA score of 0.823. A total of 9,500 tweets were finally selected for the task. This set of tweets was divided into a training, a development and a test set. Table 1 shows the distribution and statistics of the corpus.

| Corpus name          | Documents | Annotations | Tokens          |
|----------------------|-----------|-------------|-----------------|
| Training             | 5,000     | 15,173      | 211,555         |
| Development          | 2,500     | 4,252       | 84,478          |
| Test                 | 2,000     | 3,859       | 70,244          |
| **Total**            | **9,500** | **23,284**  | **366,277**     |

| SocialDisner-Diseases | 85,077 | 116,260 | 3,236,411 |
| SocialDisner-Symptoms | 12,624 | 12,896 | 521,503  |
| SocialDisner-Procedures | 11,464 | 10,080 | 467,059  |
| SocialDisner-Pharma | 1,759  | 1,029 | 68,269   |
| SocialDisner-Morphology_neoplasms | 8,518 | 8,943 | 332,539  |
| SocialDisner-Professions | 15,831 | 18,590 | 660,071  |
| SocialDisner-Person | 41,033 | 58,007 | 1,689,479 |
| SocialDisner-Species | 12,118 | 14,014 | 486,249  |

Table 1: SocialDisNER corpora summary.

3.2 **SocialDisNER Large Scale corpus**
A set of 85,000 tweets was selected to generate large-scale corpora of Spanish tweets with several biomedical mentions. These datasets were published as Silver Standard and were generated using NER systems trained on data previously published by our team. Since those NERs were not trained with tweets, programmatic cleanups were performed by eliminating mentions containing URLs and more than one twitter mention. Additionally, we conducted a manual review of the most recurrent mentions to eliminate false positives. The statistics for each large-scale corpus are shown in Table 1. Due to the selection process of the SocialDisNER data, which focused on diseases, there is a higher presence of content with this entity.

3.3 **SocialDisNER co-mention networks**
Inspired by (Hope et al., 2020), several co-occurrence matrices of mentions present in the large-scale corpus have been made available to the community. On the one hand, we have published a disease co-occurrence matrix, which could be used to analyze the comorbidity of diseases among users. Co-mention matrices between diseases and other entities have also been published, providing interesting associations between diseases and symptoms, professions and medicines, among others. To the best of our knowledge, this is the first graph of social network biomedical mentions in Spanish.

3.4 **SocialDisNER guidelines**
We have also published the SocialDisNER guidelines. This document shows the annotation criteria used by medical experts when creating the corpus and ensure its quality and replicability. The guidelines were created by adapting the DisTEMIST annotation rules to the special features of social me-
dia. The final version contains 56 annotation and restriction rules in relation to disease concepts. The guidelines are freely available at Zenodo (Farré-Maduell et al., 2022).

4 Results

Participation. SocialDisNER achieved a considerable impact in the scientific-technical community. A total of 47 teams were registered, out of which 17 submitted a total of 32 runs for evaluation. Although most of the teams came from academic environments, a significant number (4) came from industry. Interestingly, 10 teams came from non-Spanish-speaking countries, which indicates the community interest in developing systems in languages other than English.

Results. Table 2 shows the results of SocialDisNER. Eleven teams achieved better performance than the baseline of the task. The best performing system was developed by the CASIA team, with a micro-average F1-score of 0.891. The Clac team obtained the best performance in terms of Recall, with a value of 0.888. The top-performing team developed a Unified Named Entity Recognition system by following a continual pre-training strategy based on transformers architecture. This system was able to correctly predict ≥93% (2871/3083) of disease mentions from the test set that also appeared in the training. Out of 776 mentions that the model had not previously seen, it was able to properly predict 511 (≈66%).

Error analysis. In common with similar biomedical entity recognition tasks, the longer the mentions, the more difficult is for models to predict them correctly (Augenstein et al., 2017). In SocialDisNER we have found a correlation of -0.24 between the prediction errors of the systems and the length of the mentions, with a tendency to error when the length of the mention increases. Regarding specific issues of detection, we have detected 4 common detection problems in several participating systems:

1. Difficulty recognizing capitalized mentions: Systems are able to detect a lowercase mention, but not its uppercase version if they have not seen it before in the training set.
2. Mentions containing punctuation marks and/or special Twitter characters: Mentions with internal punctuation marks are difficult to be correctly extracted by systems. They are usually detected as several independent mentions or detecting only one of the segments.
3. Composite mentions: Mentions that refer to more than one disease using conjunctions or prepositions are noted as a single mention, but participating systems tend to split such mentions when extracted.

Table 2: SocialDisNER ranking with the best submission per team. Best result bolded, second best underlined. A/I stands for Academy/Industry.

| Team       | Country | A/I | Tool          | P  | R  | F1  | Ref                                      |
|------------|---------|-----|---------------|----|----|-----|------------------------------------------|
| CASIA      | China   | A   | -             | 0.906 | 0.876 | 0.891 | (Fu et al., 2022)                        |
| READ-BioMed| Australia| A | (READ-BioMed, 2022) | 0.868 | 0.875 | 0.871 | (Yepes and Verspoor, 2022)               |
| Clac       | Canada  | A   | -             | 0.851 | 0.888 | 0.869 | (Verma et al., 2022)                    |
| PLN CMM    | Chile   | A   | (PLN-CMM, 2022) | 0.882 | 0.843 | 0.862 | (Rojas et al., 2022)                    |
| NLP-CIC-WFU| México  | A   | (Tamayo, 2022)  | 0.842 | 0.860 | 0.851 | (Tamayo et al., 2022)                   |
| dezzai     | Spain   | I   | -             | 0.828 | 0.845 | 0.836 | (Ortega-Martín et al., 2022)            |
| RACAI      | Romania | A   | (RACAI, 2022)  | 0.868 | 0.779 | 0.821 | (Avram et al., 2022)                    |
| KU_EDI     | Korea   | A   | -             | 0.809 | 0.798 | 0.803 | (Lain et al., 2022)                     |
| SINAI      | Spain   | A   | (SINAI, 2022)  | 0.756 | 0.795 | 0.775 | (Chizhikova et al., 2022)               |
| ITAINNOVA  | Spain   | I   | (ITAINNOVA, 2022) | 0.779 | 0.769 | 0.774 | (Montaño-Salas et al., 2022)            |
| FRE        | Spain   | I   | -             | 0.680 | 0.805 | 0.738 | (Cetina and García-Santa, 2022)         |
| baseline   | (TeMU-BSC, 2022) |    | 0.776 | 0.701 | 0.737 |                                          |

* Same system that the one used in DisTEMIST.
* The best system of this team was a post-workshop evaluation.
* This team had problems in the evaluation phase due to the format used in the submission.
4. Detection of mention boundaries: The systems developed in the task predict longer mentions than expected when there are symbols such as hashtag "#" or emojis before and/or after the mention.

Some examples of these errors can be found in Table 3 in appendix A. The systems also fail to properly detect mentions semantically similar to those seen in the training phase, but expressed with another verbal construction. For example, the models are able to detect "suicide" but not "thinking about suicide".

5 Discussion

SocialDisNER is the first task focused on extracting diseases from social media content written in Spanish. The first Gold Standard corpus of tweets with diseases annotated by medical experts has been built specially for the task. The corpus documents were selected to contain first-person patient experiences and relevant biomedical information written by experts.

We also published additional resources such a large-scale Silver Standard corpus annotated with additional biomedical entities that might be used to train systems to detect entities in Spanish tweets that previously could not be detected due to lack of resources. This large-scale corpus made it possible to generate co-mention networks that can be used toward Knowledge Graph mining to replicate studies on adverse drug effects in Spanish-speaking people (Nikfarjam et al., 2015). A knowledge graph similar to the one in Figure 2 might allow descriptive analysis of disease co-morbidities, to detect new symptoms in rare diseases, to discover diseases associated with specific professions, and even to discover adverse effects of biomaterials and prosthetics.

SocialDisNER has been very well received by the community. There have been participants from the academy and the industry, probably enticed by the methodology followed to collect content, which ensured that a significant percentage of the documents were of high relevance. Nevertheless, the modularity with which the methodology has been defined enables its improvement for future shared-tasks and projects. For example, more sophisticated first-person detection systems such as those developed in Al-Garadi et al. (2020) could be used, based on manual annotation of previous data. NER systems could also be trained with the large-scale corpus to improve the data enrichment process. This data selection methodology to retrieve relevant information could also be easily transferred to other languages as it relies on the presence of patient associations on Twitter, which is relatively common.

When organizing the task, we contacted several patient associations with Twitter accounts. These groups showed interest in SocialDisNER, its results and how the output of the task may benefit the patients. The interest shown by associations, which in many cases helped to disseminate the event, shows the importance of involving all relevant stakeholders during the development and organization phases in order to increase the impact and use cases of our work.

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### Appendix prediction errors

| Name | Tweet with mention | Example of participants extraction |
|------|--------------------|------------------------------------|
| Capitalized mentions | LAS CICATRICES No hay cicatriz, (...) | Systems predict the mention "cicatrices", but not "CICATRICES", only present in the test set. |
| | (...) NO SOMOS DEPRESIVAS, TENEMOS DEPRESIÓN! Sabías (...) | Systems predict "depresión", but not "DEPRESIÓN" |
| Mentions with punctuation marks and/or special characters | visibilidad para esta enfermedad crónica asociada al #dolor | enfermedad crónica enfermedad crónica and dolor |
| | (...)teniendo una enfermedad crónica (Crohn) y en tratamiento(...) | enfermedad crónica enfermedad crónica (Crohn) enfermedad crónica and Crohn |
| | (...)Antraciclinas en Her2+ en ca de mama temprano(...) | ca de mama ca de mama temprano her2 and de mama |
| Composite mentions | (...)debido a una malformación o disfunción de los órganos que(...) | malformación disfunción de los órganos malformación o disfunción de los órganos |
| | (...)cuidar a su marido con cáncer y metástasis. No(...) | cancer and metástasis |
| Detection of mention boundaries | (...)y el consiguiente dato NEURONAL... | dato NEURONAL |
| | (...)lo agradecemos 😊😊😊😊 ConferenciaCovid19 (...) | ConferenciaCovid19 |

Table 3: Example of prediction errors of SocialDisNER systems