Overview of the Shared Task on Hope Speech Detection for Equality, Diversity, and Inclusion

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Abstract

Hope Speech detection is the task of classifying a sentence as hope speech or non-hope speech given a corpus of sentences. Hope speech is any message or content that is positive, encouraging, reassuring, inclusive and supportive that inspires and engenders optimism in the minds of people. In contrast to identifying and censoring negative speech patterns, hope speech detection focused on recognising and promoting positive speech patterns online. In this paper, we report an overview of the findings and results from the shared task on hope speech detection for Tamil, Malayalam, Kannada, English and Spanish languages conducted at the second workshop on Language Technology for Equality, Diversity and Inclusion (LT-EDI-2022), organised as a part of ACL 2022. The participants were provided with annotated training & development datasets and unlabelled test datasets in all five languages. The goal of the shared task is to classify the given sentences into one of the two hope speech classes (Hope speech, Non hope speech). A total of 126 participants registered for the shared task and 14 teams finally submitted their results. The performance of the systems submitted were evaluated in terms of micro-F1 score and weighted-F1 score. The datasets for this challenge are openly available at the competition website[1].

[1]https://competitions.codalab.org/competitions/36393#learn_the_details-evaluation

1 Introduction

Social media platforms such as Facebook, Twitter, Instagram and YouTube have attracted millions of people to share content and express their opinions. These platforms also serve as a medium for marginalised people who want to receive online help and support from others (Gowen et al., 2012; Yates et al., 2017; Wang and Jurgens, 2018). With the pandemic outbreak, the population from several parts of the world is affected by the fear of losing their loved ones and the loss of access to basic services such as schools, hospitals and mental health care centres (Pérez-Escoda et al., 2020). As a result, people turn to online forums to meet their informational, emotional, and social needs (Elmer et al., 2020). Online social networking sites provide a platform for people to network, feel socially included, and gain a sense of belonging as part of a community. People's physical and psychological well-being, as well as mental health, are greatly influenced by these factors (Chung, 2013; Altszyler et al., 2018; Tortoreto et al., 2019).

Although social media platforms have these positive aspects, social media content also has a large amount of spiteful or negative posts due to the lack of any mediating authority (Sampath et al., 2022; Ravikiran et al., 2022; Chakravarthi et al., 2022; Bharathi et al., 2022; Priyadharshini et al., 2022). In order to tackle this problem, social media posts are analysed to identify and control the spread of

Proceedings of the Second Workshop on Language Technology for Equality, Diversity and Inclusion, pages 378 - 388

negative content using methods such as hate speech detection(Schmidt and Wiegand, 2017), offensive language identification (Zampieri et al., 2019; Kumaresan et al., 2021), homophobia/transpohibia detection (Chakravarthi et al., 2021) and abusive language detection (Lee et al., 2018). Technologies focused on curbing hate speech and offensive language have their own drawbacks, such as training data bias (Davidson et al., 2019), and controlling user expression by imposing barriers on modes of speech, thus affecting the principles of Equality, Diversity and Inclusion. Therefore, we turn our attention towards spreading positivity rather than curbing individual expression to address negative comments.

To this end, last year, we organised the first shared task on Hope Speech Detection for Equality, Diversity and Inclusion in EACL 2021 for English and two under-resourced languages Tamil and Malayalam (Chakravarthi and Muralidaran, 2021). The English dataset contained monolingual YouTube comments, while those of Tamil and Malayalam contained code-mixed comments. Continuing our efforts in this direction, this year, we have organised the second shared task on Hope Speech Detection by extending the dataset with two additional languages, Kannada and Spanish. It has been launched at the second workshop on Language Technology for Equality, Diversity and Inclusion (LT-EDI-2022), held as a part of ACL 2022.

In the context of this shared task, hope speech refers to any social media comment that is positive, encouraging, reassuring, inclusive or supportive that inspires and engenders optimism in people's minds. Hope speech detection refers to the task of classifying a given comment into one of the following classes Hope_speech or Non_hope_speech. The participants of the shared task were provided with development, training and testing datasets in all the five languages. The comments in Tamil, Kannada and Malayalam datasets were code-mixed (Chakravarthi et al., 2020). This is because the dataset consists of YouTube comments and it is very common for speakers of these languages to use code-mixed language in online interactions. We conducted the shared task as a post/comment-level classification task. In this paper, we present the overview of the dataset, the results of the competing systems, and the findings of this shared task.

The CodaLab competition website[2] will remain open to allow researchers to access the datasets and build upon this work.

2 Task Description

The goal of the proposed shared task is to classify a given social media comment as *hope speech* or *non-hope speech*. The participants were provided with training, development, and test datasets in five languages (English, Tamil, Malayalam, Kannada, and Spanish). The annotations of the datasets were made at the comment/post level. A comment/post may contain more than one sentence, but the average sentence length of the corpus is one. The participants could choose to take part in classifying one or more languages. Leader-board results were published for each language. Some sample sentences from the datasets and their annotations are provided below. The comments have also been translated into standard English for the benefit of the reader.

- **Bruh these LGBT people gotta chill with this little girl** - *Brother, these LGBT people have to chill with this little girl.* **Non_hope_speech**.
- **Idu charitre srustiso avatara super sir**- *This is an avatar that is will create history. Superb, sir!* **Hope_speech**
- **Munbotte yellvidha sawbhagiyavum undakatte**- *I wish you all the best things in future* **Hope_speech**
- **Ithu ennada kanndraavi**- *What kind of nonsense is this!* **Non_hope_speech**
- **Friendly reminder: las personas #LGTBI, al igual que todas las demás, tenemos derecho de legítima defensa.**- *Friendly reminder: #LGTBI people, like everyone else, have the right to self-defense.* **Hope_speech**

3 Datasets

The corpus provided in this shared task consists of a total of 63,883 social media comments in five different languages. There are 28,424 comments in English, 17,715 in Tamil, 9,918 in Malayalam,

[2] https://competitions.codalab.org/competitions/36393#learn_the_details-evaluation

6,176 in Kannada and 1,650 comments in Spanish. Since the datasets consist of comments from social media such as YouTube and Twitter, some sentences contains @ names, repeated letters or words, symbols, special characters, etc.

For English, Tamil and Malayalam languages we used the HopeEDI dataset from (Chakravarthi, 2020). The data was collected on a wide range of socially relevant topics such as Equality, Diversity and Inclusion, including LGBTIQ issues, COVID-19, women in STEM, Dravidian languages, Black Lives Matter, etc. The inter-annotator agreement was verified using Krippendorf's alpha.

The Kannada hope speech dataset contains 6,176 posts collected from YouTube video comments on various topics, such as social oppression, marginalisation and mental health, Indo-China border issues, or the banning of mobile apps in India. The details of dataset construction, corpus statistics, inter-annotator agreement and code-mixing issues are presented in detail in (Hande et al., 2021).

The Spanish Hope Speech dataset consists of LGTBI-related tweets that were collected using the Twitter API (June 27, 2021 to July26, 2021). As seed for the search a lexicon of LGBITQ-related terms, such as #OrgulloLGTBI or #LGTB was used. A tweet is marked as HS (Hope Speech) if the text: i) explicitly supports the social integration of minorities; ii) is a positive inspiration for the LGTBI community; iii) explicitly encourages LGTBI people who might find themselves in a situation; or iv) unconditionally promotes tolerance. On the contrary, a tweet is marked as NHS (Non Hope Speech) if the text: i) expresses negative sentiment towards the LGTBI community; ii) explicitly seeks violence; or iii) uses gender-based insults.

Table 1 shows the corpus statistics and Table 2 the distribution of the data by class and set, both showing the data in terms of language. The annotated datasets were divided into training, development and test sets to contain approximately 80%, 10% and 10% of the total number of comments. The corpus statistics were calculated using *nltk* tool (Bird, 2006). There are more non hope speech comments than hope speech. This makes the datasets imbalanced and skewed more towards one class than the other, which the participants had to take into account when developing their classification systems.

4 Task Settings

4.1 Training Phase

During the training phase, we provided participants with labelled training and development data that they could use to train and validate their models. We released the data for all the languages and the participants were able to whether they wanted to participate in developing models for more than one language. The goal of this phase was to provide the participants with sufficient data that they could used to perform cross-validation for their preliminary evaluations and hyperparameter setting. This ensured that participants were ready for evaluation before the release of the unlabeled test data. A total of 126 participants registered for the shared task and downloaded the datasets in this phase.

4.2 Testing Phase

During the testing phase, the participants were given test data without the gold labels. Each participating team was allowed as many submissions as they could, from which the best result was considered for preparing the leaderboard ranking. The submission outputs were compared with the gold standard labels and the macro and weighted-average versions of precision, recall and F1-score were reported for all the classes. The ranking list was prepared based on the best performance measured on the macro F1-scores. In this phase, there were 13,7,9,6,7 participants who submitted their results for English, Kannada, Malayalam, Spanish and Tamil, respectively.

5 Systems

We begin this section by presenting a brief summary of the baselines established for this shared task based on the submissions received last year. We then briefly describe each of the proposals submitted this year. Readers are encouraged to consult the participants' individual papers for a more detailed understanding.

5.1 Baseline results from LT-EDI 2021

In 2021, the shared task on Hope Speech Detection as a part of LT-EDI workshop received 31,31 and 30 submissions for English, Malayalam and Tamil, respectively. It was a three-class classification task in which the class labels were "Hope", "Non-hope", and "Not Tamil/ Not English/ Not Malayalam". XLM-Roberta was the popular choice among most of the top performing teams. Other participants

	Language				
	English	Tamil	Malayalam	Kannada	Spanish
Number of words	522,717	191,212	122,917	56,549	60,058
Vocabulary size	29,383	46,237	40,893	18,807	12,018
Number of comments/tweets	28,424	17,715	9,918	6,176	1,650
Number of sentences	46,974	22,935	13,643	6,871	2,886
Avg. words per sentence	18	9	11	9	21
Avg. sentences per comment/tweet	1	1	1	1	2

Table 1: Datasets statistics

Data	Class	Language					Total
		English	Tamil	Malayalam	Kannada	Spanish	
Training	Hope speech	1,962	6,327	1,668	1,699	491	12,147
	Non hope speech	20,778	7,872	6,205	3,241	499	38,595
Development	Hope speech	272	757	190	210	169	1,598
	Non hope speech	2,569	998	784	408	161	4,920
Test		2,843	1,761	1,071	618	330	6,623
Total		28,424	17,715	9,918	6,176	1,650	63,883

Table 2: Data distribution by class and set

used models such as context-aware string embeddings for word representation, Recurrent Neural Networks and pooled document embeddings for text representation, Bi-LSTM, and different machine learning and deep learning models.

Upadhyay et al. (2021) used a voting ensemble approach with 11 models and fine-tuned pre-trained transformer models to get an F1-score of 0.93. Transformer methods were proposed with fine-tuned methods such as RoBERTa (Mahajan et al., 2021), XML-R (Hossain et al., 2021), XML-RoBERTa (Ziehe et al., 2021), XML-RoBERTa with TF-IDF (Huang and Bai, 2021), ALBERT with K-fold cross validation (Chen and Kong, 2021) and multilingual BERT model with convolution neural networks (Dowlagar and Mamidi, 2021). (M K and A P, 2021) showed comparable results by using a combination of contextualised string embedding, stacked word embeddings and pooled document embedding with Recurrent Neural Network.

Chinnappa (2021) used FNN, BERT and SBERT to classify the comments into one of the two labels after performing language detection which achieved an F1-score of 0.92. Balouchzahi et al. (2021) solved the problem by using character sequences for words in code-mixed Malayalam and Tamil comments and by using a combination of word and character n-grams for English comments to get an F1-score of 0.92 for English. The F1-scores do not present the full picture of the quality of these models because none of these models gave an F1-score of more than 0.60 for "Hope" class which means that the high F1-scores were due to the fact that most of the comments in the dataset were in "Non-hope" class. The top scores were 0.61, 0.85 and 0.93 for Tamil, Malayalam and English respectively. From the previous shared task, it was observed that the number of "Non-hope" labels in Tamil dataset is comparable to the number of "Not Tamil" labels in last year's dataset as opposed to English and Malayalam which made the classification in these two languages as a binary classification task instead of three classes. The shared task of this year is a binary classification problem for all the five languages. A summary of each of the submission this year is presented briefly in the upcoming subsection.

5.2 Systems Description

In this section, we summarise the systems submitted by the participants of the shared task. A short discussion on the methodology used in each submission is presented here.

CIC@LT-EDI-ACL2022 (Balouchzahi et al., 2022) participated in identifying Hope Speech classes in English and Spanish. Their model consists of a basic sequential neural network with the combination of features including Linguistic Enquiry and Word Count (LIWC) and n-grams. They developed a deep learning approach which ranked 2nd in English and 3rd in Spanish for hope speech detection. They also identified psycho-linguistic

Team-Name	M_P	M_R	M_F1	W_P	W_R	W_F1	Rank
IIITSurat	0.560	0.540	0.550	0.870	0.890	0.880	1
MUCIC (M D Gowda et al., 2022)	0.540	0.550	0.550	0.870	0.850	0.860	1
ARGUABLY	0.550	0.540	0.540	0.870	0.880	0.870	2
CIC (Balouchzahi et al., 2022)	0.540	0.530	0.530	0.860	0.870	0.870	3
LeaningTower (Muti et al., 2022)	0.530	0.530	0.530	0.860	0.870	0.870	3
CUNI-TIET	0.510	0.520	0.510	0.860	0.820	0.840	4
ginius (Chinagundi and Surana, 2022)	0.510	0.510	0.510	0.860	0.860	0.860	4
Ablimet	0.410	0.410	0.410	0.880	0.880	0.880	5
SSN_ARMM (V et al., 2022)	0.420	0.410	0.410	0.880	0.890	0.880	5
LPS (Ying Zhu, 2022)	0.420	0.410	0.410	0.880	0.890	0.880	5
SSNCSE_NLP (Srinivasan et al., 2022)	0.430	0.390	0.400	0.870	0.900	0.880	6
error_english	0.440	0.390	0.400	0.880	0.900	0.890	6
SOA_NLP (Kumar et al., 2022)	0.460	0.370	0.380	0.880	0.910	0.880	7

Table 3: Rank list based on Macro F1-score along with other evaluation metrics (Macro Precision, Recall and Weighted Precision, Recall and F1-score) for English language

Team-Name	M_P	M_R	M_F1	W_P	W_R	W_F1	Rank
Ablimet	0.300	0.340	0.320	0.390	0.460	0.420	1
LPS (Ying Zhu, 2022)	0.290	0.340	0.310	0.390	0.440	0.410	2
ARGUABLY	0.290	0.330	0.300	0.380	0.440	0.400	3
SSN_ARMM (V et al., 2022)	0.280	0.320	0.300	0.370	0.420	0.390	3
SSNCSE_NLP (Srinivasan et al., 2022)	0.280	0.330	0.300	0.370	0.440	0.400	3
CEN	0.280	0.330	0.300	0.370	0.440	0.390	3
SOA_NLP (Kumar et al., 2022)	0.280	0.320	0.290	0.360	0.430	0.380	4

Table 4: Rank list based on Macro F1-score along with other evaluation metrics (Macro Precision, Recall and Weighted Precision, Recall and F1-score) for Tamil language

Team-Name	M_P	M_R	M_F1	W_P	W_R	W_F1	Rank
ARGUABLY	0.640	0.530	0.500	0.760	0.790	0.750	1
SSN_ARMM (V et al., 2022)	0.470	0.500	0.490	0.700	0.780	0.740	2
SOA_NLP (Kumar et al., 2022)	0.520	0.480	0.480	0.720	0.790	0.740	3
CEN	0.520	0.470	0.480	0.720	0.790	0.740	3
Ablimet	0.450	0.520	0.480	0.700	0.760	0.730	3
LPS (Ying Zhu, 2022)	0.450	0.490	0.470	0.690	0.760	0.720	4
SSNCSE_NLP (Srinivasan et al., 2022)	0.440	0.470	0.450	0.680	0.750	0.710	5
YUN111	0.310	0.340	0.320	0.560	0.600	0.580	6
MUCIC (M D Gowda et al., 2022)	0.310	0.320	0.310	0.560	0.580	0.570	7

Table 5: Rank list based on Macro F1-score along with other evaluation metrics (Macro Precision, Recall and Weighted Precision, Recall and F1-score) for Malayalam language

Team-Name	M_P	M_R	M_F1	W_P	W_R	W_F1	Rank
SSN_ARMM (V et al., 2022)	0.480	0.470	0.480	0.740	0.760	0.750	1
Ablimet	0.460	0.480	0.470	0.730	0.720	0.730	2
SOA_NLP (Kumar et al., 2022)	0.490	0.470	0.470	0.740	0.760	0.750	2
LPS (Ying Zhu, 2022)	0.450	0.450	0.450	0.710	0.710	0.710	3
SSNCSE_NLP (Srinivasan et al., 2022)	0.450	0.440	0.440	0.700	0.720	0.700	4
ARGUABLY	0.310	0.320	0.320	0.530	0.540	0.540	5
MUCIC (M D Gowda et al., 2022)	0.310	0.310	0.310	0.520	0.530	0.520	6

Table 6: Rank list based on Macro F1-score along with other evaluation metrics (Macro Precision, Recall and Weighted Precision, Recall and F1-score) for Kannada language

Team-Name	M_P	M_R	M_F1	W_P	W_R	W_F1	Rank
ARGUABLY	0.810	0.810	0.810	0.810	0.810	0.810	1
Ablimet	0.800	0.800	0.800	0.800	0.800	0.800	2
CIC (Balouchzahi et al., 2021)	0.790	0.790	0.790	0.790	0.790	0.790	3
SOA_NLP (Kumar et al., 2022)	0.790	0.790	0.790	0.790	0.790	0.790	3
SSNCSE_NLP (Srinivasan et al., 2022)	0.790	0.790	0.790	0.790	0.790	0.790	3
LPS (Ying Zhu, 2022)	0.770	0.760	0.760	0.770	0.760	0.760	4

Table 7: Rank list based on Macro F1-score along with other evaluation metrics (Macro Precision, Recall and Weighted Precision, Recall and F1-score) for Spanish language

and linguistic features that work the best for the two languages. They found that the overall Macro F1 scores achieved in the English task was significantly lower than the Weighted F1 score because of the imbalanced classes contrary to Spanish texts where the classes were balanced.

LPS@LT-EDI-ACL2022 (Ying Zhu, 2022) submitted results for all the five languages. All the data submitted came from the same model framework and the same system architecture which is an ensemble model consisting of three parts. These are LSTM, CNN+LSTM and BiLSTM, respectively. Finally, an attention layer is added before the ensemble of the three-part results. The introduction of the attention mechanism not only helped the model to make better use of the effective information in the input, but also provided some ability to explain the behavior of the neural network model.

CURAJ_IIITDWD@LTEDIACL 2022 (Jha et al., 2022) worked on the dataset of English hope speech comments. The studies were conducted using a multilayer neural network, one layer CNN, one layer Bi-LSTM, and one layer GRU, among the deep learning networks. The stacked networks of LSTM-CNN and LSTM-LSTM were also trained. The stacked LSTM-LSTM network and DNN produced the best results with Weighted F1-score of 0.89. All of the experiments were carried out in the Keras and sklearn environment. They used the pandas library to read the datasets. Keras preprocessing classes and the nltk library were used to prepare the dataset.

giniUs@LT-EDI-ACL2022 (Chinagundi and Surana, 2022) used the transformer-based pretrained models along with the customized versions of those models with custom loss functions. Their best configurations for the shared tasks achieved weighted F1 scores of 0.60 for Tamil, 0.83 for Malayalam, and 0.93 for English. They have secured ranks of 4, 3, 2 in Tamil, Malayalam and English respectively. They experimented with prominently known models namely BERT-Base-Uncased, RoBERTa-Base, RoBERTa-Large. They found that RoBERTa-Large performs the best when the last four layers of the language model are concatenated for a deeper embedding representation, which is then passed through a pre classifier and a RELU activation layer followed by a dropout layer before finally coming across the classification head for the labels that are to be predicted.

IDIAP_TIET@LT-EDI-ACL2022 focused on the English comments. Motivated by the efficiency of transformers in NLP, they encoded the comments using the BERT language model and created an embeddings matrix. Further, this embeddings matrix was fed to the attention network, trained to classify for Hope Speech. The proposed model has proven to be remarkable by achieving fourth position on the leaderboard with a difference of 0.04 in F1-score from the top-performing model.

IIITSurat@LT-EDI-EACL2022 worked on the English dataset. Their model works in two phases: firs, it uses over-sampling techniques to increase the number of samples and make them comparable in the training dataset, followed by a random forest classifier to classify the comments into hope and non-hope categories. The proposed model achieved a macro F1-score of 0.55 on the test dataset and secured the first place among the participating teams.

IIT Dhanbad @LT-EDI-ACL2022 (Gupta et al., 2022) worked on the English dataset. They have used various machine learning algorithms, namely - Logistic Regression, Multinomial Naive Bayes classifier, Random forest classifier and XGBoost. They have used the scikit-learn library for logistic regression, Multinomial NB and Random forest classifiers. The best score as Macro-F1 for the task achieved by the team is 0.6130. The XGBoost system is their best performing model.

LeaningTower@LT-EDI-ACL2022 (Muti et al., 2022) targeted the task in English by using reinforced BERT-based approaches. The core strategy aimed at exploiting the data available for homophobic and transphobic comment detection to augment the number of supervised instances in the Hope Speech Detection task. On the basis of an active learning process, the team trained a model on the dataset for hope speech detection task and applied it to the dataset for homo/transphobia detection task to iteratively integrate new silver data for hope speech task. Their submission to the shared task obtained a macro-averaged F1 score of 0.53, placing the team in the third rank.

MUCIC@LT-EDI-ACL2022 (M D Gowda et al., 2022) dealt with data sets provided in English, Kannada and Tamil. Their methodology used the resampling technique to deal with imbalanced data in the corpus and obtained 1st rank for the English language with an average macro F1-035 score of 0.550 and weighted F1-score of 0.860.

SOA_NLP@LT-EDI-ACL2022 (Kumar et al., 2022) participated in the task covering all the languages – English, Spanish, Kannada, Tamil and Malayalam. The proposed ensemble model combined three machine learning algorithms: (i) Support Vector Machine (SVM), (ii) Logistic Regression (LR), and (iii) Random Forest (RF). The efficiency of different combinations of n-gram char-level and word-level TF-IDF features were also explored in the identification of hope speech.

SSN_ARMM@ LT-EDI-ACL2022 (V et al., 2022) worked on the dataset in English, Tamil, Malayalam and Kannada. They used the IndicBERT model which is a multilingual model trained on large-scale corpora covering 12 Indian languages. IndicBERT takes a smaller number of parameters and still manages to give state-of-the-art performance.

SSNCSE_NLP@LT-EDI-ACL2022 (Srinivasan et al., 2022) participated in the shared task covering English, Malayalam, Kannada and Tamil languages. They employed several machine learning transformer models such as m-BERT, MLNet, BERT, XLMRoberta, XLM_MLM. The results indicated that BERT, and m-BERT obtained the best performance among all the other techniques, gaining a weighted F1- score of 0.92, 0.71, 0.76, 0.87, and 0.83 for English, Tamil, Spanish, Kannada and Malayalam respectively.

6 Results and discussion

The total of submissions received for the classification of English, Tamil, Malayalam, Kannada and Spanish datasets were 13,7,9,7 and 6 respectively. Three teams submitted their results for all the languages, while the other participants made their submissions for a subset of the languages. Two teams obtained first rank in English with a macro average of 0.550. One of them (M D Gowda et al., 2022) used a resampling technique to deal with imbalanced data and 1D CNN-LSTM architecture to address the classification problem. The other team used Random Forest Classifier to classify the comments. Transformer-based pretrained models were used in five studies out of which one of them used multilingual IndicBERT model for classifying English, Tamil, Malayalam and Kannada languages. This model achieved first and second ranks on Kannada and Malayalam languages respectively.

Among other submissions, the popular choice was an ensemble of various Machine Learning classifiers such as Logistic Regression, Multinomial Naive Bayes, Random Forest, Support Vector Machines. However, we observed that the performances of the ML classifiers used for this shared task were slightly lower than the baseline performances of ML models used last year. LSTM, BiL-

STM, CNN were used but their performance were not as good as the transformer based models.

7 Conclusion

This paper presents the description of the second Shared Task on Hope Speech Detection for Equality, Diversity and Inclusion organized at the second workshop on Language Technology for Equality, Diversity and Inclusion (LT-EDI-2022), held as a part of ACL 2022. In the 2021 edition this shared task was organized for English and two under-resourced languages, Tamil and Malayalam, and for this edition, two new languages, Kannada and Spanish, have been incorporated. In total, 126 participants signed up for the for the shared task and finally 13,7,9,6, and 7 teams submitted their results for English, Kannada, Malayalam, Spanish and Tamil, respectively. We hope that this shared task makes a lasting contribution to the NLP field.

Acknowledgements

Authors Bharathi Raja Chakravarthi and John Phillip McCrae were supported in part by a research grant from Science Foundation Ireland (SFI) under Grant Number SFI/12/RC/2289_P2 (Insight_2), co-funded by the European Regional Development Fund and Irish Research Council grant IRCLA/2017/129 (CARDAMOM-Comparative Deep Models of Language for Minority and Historical Languages).

Salud María Jiménez-Zafra was supported by Fondo Social Europeo and Administration of the Junta de Andalucía (DOC_01073). Rafael Valencia-García was supported by project LaTe4PSP (PID2019-107652RB-I00) funded by MCIN/AEI/10.13039/501100011033, and Project AlInFunds (PDC2021-121112-I00) funded by MCIN/AEI/10.13039/501100011033 and by the European Union NextGenerationEU/PRTR. Miguel Ángel García-Cumbreras and Salud María Jiménez-Zafra were supported by Project LIVING-LANG (RTI2018-094653-B-C21) funded by MCIN/AEI/10.13039/501100011033 and by ERDF A way of making Europe. Salud María Jiménez-Zafra was supported by Project PID2020-116118GA-I00 funded by MICINN/AEI/10.13039/501100011033, and Project PID2020-119478GB-I00 funded by MICINN/AEI/10.13039/501100011033. José Antonio García-Díaz was supported by Banco Santander and University of Murcia through the industrial doctorate programme. Miguel Ángel García-Cumbreras and Salud María Jiménez-Zafra were supported by Grant P20_00956 (PAIDI 2020) and grant 1380939 (FEDER Andalucía 2014-2020) from the Andalusian Regional Government.

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