Overview of the Fifth Social Media Mining for Health Applications (#SMM4H) Shared Tasks at COLING 2020

Ari Z. Klein
University of Pennsylvania
Philadelphia, PA, USA

Ilseyar Alimova
Kazan Federal University
Kazan, Russia

Ivan Flores
University of Pennsylvania
Philadelphia, PA, USA

Arjun Magge
University of Pennsylvania
Philadelphia, PA, USA

Zulfat Miftahutdinov
Kazan Federal University
Kazan, Russia

Anne-Lyse Minard
University of Orléans, LLL-CNRS
Orléans, France

Karen O’Connor
University of Pennsylvania
Philadelphia, PA, USA

Abeed Sarker
Emory University
Atlanta, GA, USA

Elena Tutubalina
Kazan Federal University
Kazan, Russia

Davy Weissenbacher
University of Pennsylvania
Philadelphia, PA, USA

Graciela Gonzalez-Hernandez
University of Pennsylvania
Philadelphia, PA, USA

{ariklein, ivan.flores, arjun.magge, karoc, dweissen, gragon}@pennmedicine.upenn.edu
{alimovailseyar, zulfatmi, tutubalinaev}@gmail.com
anne-lyse.minard@univ-orleans.fr, abeed@dbmi.emory.edu

Abstract

The vast amount of data on social media presents significant opportunities and challenges for utilizing it as a resource for health informatics. The fifth iteration of the Social Media Mining for Health Applications (#SMM4H) shared tasks sought to advance the use of Twitter data (tweets) for pharmacovigilance, toxicovigilance, and epidemiology of birth defects. In addition to re-runs of three tasks, #SMM4H 2020 included new tasks for detecting adverse effects of medications in French and Russian tweets, characterizing chatter related to prescription medication abuse, and detecting self reports of birth defect pregnancy outcomes. The five tasks required methods for binary classification, multi-class classification, and named entity recognition (NER). With 29 teams and a total of 130 system submissions, participation in the #SMM4H shared tasks continues to grow.

1 Introduction

The aim of the Social Media Mining for Health Applications (#SMM4H) shared tasks is to take a community-driven approach to addressing natural language processing (NLP) challenges of utilizing social media data for health informatics, including informal, colloquial expressions of clinical concepts, noise, data sparsity, ambiguity, and multilingual posts. The fifth iteration of the #SMM4H shared tasks consisted of five tasks involving mining health-related information from Twitter data (tweets): automatic classification of tweets that mention medications (Task 1), automatic classification of multilingual tweets that report adverse effects of a medication (Task 2), with sub-tasks for distinct sets of tweets posted in English (Task 2a), French (Task 2b), and Russian (Task 2c), automatic extraction and normalization of adverse effects in English tweets (Task 3), automatic characterization of chatter related to prescription medication abuse in tweets (Task 4), and automatic classification of tweets self-reporting a birth defect pregnancy outcome (Task 5).

Teams could register for one or multiple tasks. In total, 57 teams registered for at least one task. To develop their systems, teams were provided with annotated training and validation sets of tweets for

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each task. For the final evaluation, teams were provided with an unlabeled test set for each task, and were allowed up to four days to submit the predictions of their systems to CodaLab\(^1\)—a platform that facilitates data science competitions. Each team was allowed to submit up to three sets of predictions per task. In total, 29 of the 57 registered teams submitted at least one set of predictions. More specifically, 16 teams participated in Task 1 (40 submissions), 17 teams in Task 2a (35 submissions), 5 teams in Task 2b (7 submissions), 7 teams in Task 2c (14 submissions), 7 teams in Task 3 (15 submissions), 3 teams in Task 4 (9 submissions), and 4 teams in Task 5 (10 submissions). In Section 2, we will briefly describe the tasks. In Section 3, we will present the performance and a brief summary of each team’s best-performing system for each task. Appendix A provides the system description papers corresponding to the team numbers used in Section 3.

2 Tasks

2.1 Task 1: Automatic Classification of Tweets that Mention Medications

Task 1 is a binary classification task that involves distinguishing tweets that mention a medication or dietary supplement (annotated as “1”) from those that do not (annotated as “0”). For this task, we used the definition of drug products and dietary supplements provided by the FDA (U.S. Food and Drug Administration, 2017). For the #SMM4H 2018 shared tasks (Weissenbacher et al., 2018), a data set was used that contained an artificially balanced distribution of the two classes. For #SMM4H 2020, the data set represents their natural, highly imbalanced distribution (Weissenbacher et al., 2019). Evaluating classifiers on this data set models more closely the detection of tweets that mention medications in practice. The training set contains 69,272 tweets, with only 181 (0.3%) tweets that mention a medication. The 9622 training tweets from #SMM4H 2018 were also provided, with 4975 tweets that mention a medication. The test set contains 29,687 tweets, with only 77 (0.3%) tweets that mention a medication. Systems were evaluated based on the $F_1$-score for the “positive” class (i.e., tweets that mention a medication).

2.2 Task 2: Automatic Classification of Multilingual Tweets that Report Adverse Effects

Task 2 is a binary classification task that involves distinguishing tweets that report an adverse effect of a medication (annotated as “1”) from those that do not (annotated as “0”), with three sub-tasks for distinct sets of tweets posted in English, French, and Russian. The training set for the long-running, English-language version of this #SMM4H shared task contains 25,678 tweets, with 2377 (9.3%) tweets that report an adverse effect of a medication. The test set contains 4759 tweets, with 194 (4.1%) tweets that report an adverse effect. For the French sub-task, the training set contains 2426 tweets, with only 39 (1.6%) tweets that report an adverse effect. Inter-annotator agreement, based on dual annotations of 848 tweets by three annotators, was 0.61 and 0.69, for each of the two pairs of annotators.

For the Russian sub-task, the training set contains 7612 tweets, with 666 (8.7%) tweets that report an adverse effect. The test set contains 1903 tweets, with 166 (8.7%) tweets that report an adverse effect. All of the Russian tweets were dual annotated; first, three Yandex.Toloka\(^2\) annotators’ crowd-sourced labels were aggregated into a single label (Dawid and Skene, 1979), and then the tweets were labeled by a second annotator. Inter-annotator agreement was 0.49 (Cohen’s kappa). Systems were evaluated based on the $F_1$-score for the “positive” class (i.e., tweets that report an adverse effect).

2.3 Task 3: Automatic Extraction and Normalization of Adverse Effects in English Tweets

Task 3 is a named entity recognition (NER) and entity normalization task that involves detecting the span of text within a tweet that reports an adverse effect of a medication, and normalizing the adverse effect to a unique Medical Dictionary for Regulatory Activities (MedDRA)\(^3\) version 21.1 preferred term (PT) ID. The training set contains 2806 tweets, with 1829 (65%) tweets that report an adverse effect (annotated

\(\text{1}https://codalab.org/\)
\(\text{2}https://toloka.yandex.ru/\)
\(\text{3}https://www.meddra.org/\)
as “ADR”). For each tweet in the training set that reports an adverse effect, the span of text containing the adverse effect, the character offsets of that span of text, and the MedDRA ID of the adverse effect. The test set contains 1156 tweets, with 970 (84%) that report an adverse effect. Systems were evaluated based on their F$_1$-score, where a true positive is both the correct adverse effect (either partially or exactly matching the actual character offsets) and the correct MedDRA ID.

### 2.4 Task 4: Automatic Characterization of Prescription Medication Abuse Chatter in Tweets

Task 4 is a multi-class classification task that involves automatically distinguishing tweets mentioning potentially abuse-prone medications into one of four categories: (1) potential abuse/misuse (annotated as “A”), (2) non-abuse/misuse consumption (annotated as “C”), (3) medication mention only without any indication of consumption (annotated as “M”), and (4) unrelated (annotated as “U”). The medications mentioned in the tweets include prescription opioids, benzodiazepines, atypical anti-psychotics, central nervous system stimulants, and GABA (gamma aminobutyric acid) analogues. The training set contains 13,172 tweets: (1) 2133 (16%) “A” tweets, (2) 3668 (28%) “C” tweets, (3) 6843 (52%) “M” tweets, and (4) 528 (4%) “U” tweets. The test set contains 3271 tweets: (1) 503 (15%) “A” tweets, (2) 919 (28%) “C” tweets, (3) 1722 “M” (53%) tweets, and (4) 127 (4%) “U” tweets. Additional details about the data set, including the annotation process, annotation guidelines, and inter-annotator agreements, are presented in recent work (O’Connor et al., 2020). Systems were evaluated based on the F$_1$-score for the “potential misuse/abuse” (“A”) class.

### 2.5 Task 5: Automatic Classification of Tweets Reporting a Birth Defect Pregnancy Outcome

Task 5 is a multi-class classification task that involves automatically distinguishing three classes of tweets that mention birth defects (Klein et al., 2018): (1) “defect” tweets refer to the user’s child and indicate that he or she has the birth defect mentioned in the tweet (annotated as “1”); (2) “possible defect” tweets are ambiguous about whether someone is the user’s child and/or has the birth defect mentioned in the tweet (annotated as “2”); (3) “non-defect” tweets merely mention birth defects (annotated as “3”). The training set contains 18,397 tweets: 966 (5%) “defect” tweets, 1041 (6%) “possible defect” tweets, and 16,390 (89%) “non-defect” tweets. The test set contains 4602 tweets: 244 (5%) “defect” tweets, 258 (6%) “possible defect” tweets, and 4100 (89%) “non-defect” tweets. Inter-annotator agreement, based on dual annotations for 21,727 of the tweets, was 0.86 (Cohen’s kappa). Systems were evaluated based on the micro-averaged F$_1$-score for the “defect” and “possible defect” classes.

### 3 Results

#### 3.1 Task 1: Automatic Classification of Tweets that Mention Medications

Table 1 presents the precision, recall, and F$_1$-score for the “positive” class (i.e., tweets that mention a medication), for each of the 16 team’s best-performing system for Task 1. The majority of teams used a transformer-based architecture. Among these teams, the difference in performance seems to be based on the corpora used to pre-train the transformers, and the strategies used the address the high degree of class imbalance. The results suggest that imbalanced data remains a challenge for training deep neural network classifiers. The best-performing system for this task in #SMM4H 2018 (Weissenbacher et al., 2018) achieved an F$_1$-score of 0.918 (Chuhan et al., 2018) using an artificially balanced data set, while the best-performing system in #SMM4H 2020 achieved an F$_1$-score of 0.854. Nonetheless, advances in transformer-based architectures and strategies for addressing class imbalance have improved upon the baseline F$_1$-score of 0.788 (Weissenbacher et al., 2019).

#### 3.2 Task 2: Automatic Classification of Multilingual Tweets that Report Adverse Effects

##### 3.2.1 Automatic Classification of English Tweets that Report Adverse Effects

Table 2 presents the precision, recall, and F$_1$-score for the “positive” class (i.e., English tweets that report an adverse effect of a medication), for each of the 17 team’s best-performing system for Task 2a. As in Task 1, the majority of teams used a transformer-based architecture. In particular, most of the better-
Table 1: Task 1 system summaries and F$_1$-scores (F$_1$), precision (P), and recall (R) for the “positive” class (i.e., tweets mentioning medications).

| Team | F$_1$  | P    | R    | System Summary                                                                 |
|------|--------|------|------|-------------------------------------------------------------------------------|
| 8    | 0.85   | 0.84 | 0.87 | BERT, Bio+Clinical BERT, sub-corpus ensemble, SMM4H’18 corpus                |
| 3    | 0.80   | 0.77 | 0.83 | RoBERTa pre-trained on tweets, ensemble, SMM4H’18 corpus                     |
| 21   | 0.80   | 0.80 | 0.79 | RoBERTa pre-trained on tweets                                                |
| 2    | 0.77   | 0.71 | 0.83 | BERT, SMM4H’18 corpus                                                        |
| 14   | 0.76   | 0.73 | 0.79 | ELECTRA, decision tree, data augmentation, ensemble, SMM4H’18 corpus         |
| 17   | 0.76   | 0.82 | 0.70 | BERT, DrugBank                                                               |
| 18   | 0.76   | 0.77 | 0.74 | RoBERTa pre-trained on biomedical literature                                 |
| 12   | 0.74   | 0.66 | 0.83 | RoBERTa pre-trained on biomedical literature, over-sampling, SMM4H’18 corpus |
| 23   | 0.72   | 0.84 | 0.62 | BERT, BiLSTM, SMM4H’18 corpus                                                |
| 19   | 0.71   | 0.79 | 0.64 | BioBERT pre-trained on tweets, sub-corpus ensemble, class weights, SMM4H’18 corpus |
| 28   | 0.66   | 0.75 | 0.58 | NA                                                                           |
| 9    | 0.64   | 0.74 | 0.56 | decision tree, word and character 15-grams                                    |
| 29   | 0.60   | 0.57 | 0.64 | NA                                                                           |
| 6    | 0.56   | 0.86 | 0.42 | BioBERT, data augmentation, ensemble                                          |
| 22   | 0.45   | 0.57 | 0.38 | NA                                                                           |
| 16   | 0.05   | 0.02 | 0.90 | SVM, sent2vec sentence and bi-gram embeddings pre-trained on tweets, under-sampling |

Table 2: Task 2a (English) system summaries and F$_1$-scores (F$_1$), precision (P), and recall (R) for the “positive” class (i.e., tweets reporting an adverse effect of a medication).

| Team | F$_1$  | P    | R    | System Summary                                                                 |
|------|--------|------|------|-------------------------------------------------------------------------------|
| 5    | 0.58   | 0.63 | 0.54 | EnDR-BERT, ensemble                                                          |
| 10   | 0.58   | 0.52 | 0.65 | RoBERTa, SMM4H’17 and SMM4H’19 corpora                                      |
| 5    | 0.57   | 0.50 | 0.66 | RoBERTa                                                                     |
| 4    | 0.56   | 0.50 | 0.63 | RoBERTa                                                                     |
| 7    | 0.56   | 0.56 | 0.55 | RoBERTa, sub-corpus ensemble, rules                                          |
| 17   | 0.55   | 0.47 | 0.65 | BERT, DrugBank, MedlinePlus, TransE MeSH representations                    |
| 6    | 0.54   | 0.49 | 0.60 | BioBERT, data augmentation, ensemble                                          |
| 1    | 0.51   | 0.48 | 0.54 | CLAPA, BERT                                                                 |
| 22   | 0.48   | 0.44 | 0.53 | SBERT RoBERTa sentence embeddings, class weights                              |
| 2    | 0.47   | 0.58 | 0.40 | BERT, SMM4H’20 Task 3 corpus                                                |
| 19   | 0.37   | 0.26 | 0.60 | BioBERT pre-trained on tweets                                               |
| 20   | 0.35   | 0.28 | 0.46 | CNN, GloVe word embeddings pre-trained on tweets, under-sampling             |
| 16   | 0.32   | 0.19 | 0.87 | SVM, sent2vec sentence and bi-gram embeddings pre-trained on tweets, under-sampling |
| 28   | 0.31   | 0.23 | 0.51 | NA                                                                           |
| 15   | 0.31   | 0.31 | 0.31 | logistic regression, feature engineering                                      |
| 29   | 0.27   | 0.16 | 0.79 | NA                                                                           |

3.2.2 Automatic Classification of French Tweets that Report Adverse Effects

Table 3 presents the precision, recall, and F$_1$-score for the “positive” class (i.e., French tweets that report an adverse effect of a medication), for each of the five team’s best-performing system for Task 2b. The highest F$_1$-score for the French-language version of this task is considerably lower than the highest F$_1$-scores for the automatic classification of adverse effects in English (0.64) and Russian (0.51) tweets. The difficulty of this task is further underscored by the fact that two teams were not able to detect any tweets reporting an adverse effect. This difficulty may be due to the small size of the training data and the high degree of class imbalance. To address the imbalanced data, Team 22 used a Bayesian optimization approach to class weighting, and Team 16 used under-sampling of the majority class.

3.2.3 Automatic Classification of Russian Tweets that Report Adverse Effects

Table 4 presents the precision, recall, and F$_1$-score for the “positive” class (i.e., Russian tweets that report an adverse effect of a medication), for each of the seven team’s best-performing system for Task 2c. Teams 26 and 25 achieve the highest F$_1$-scores (0.51). Both teams used ensembles of BERT-based Russian language models from the DeepPavlov library (Burstein et al., 2018). In addition, both teams used manually annotated drug reviews from the RuDREC corpus (Tutubalina et al., 2020) as additional
Table 3: Task 2b (French) system summaries and F1-scores (F1), precision (P), and recall (R) for the “positive” class (i.e., tweets reporting an adverse effect of a medication).

| Team | F1  | P   | R   | System Summary                                      |
|------|-----|-----|-----|-----------------------------------------------------|
| 22   | 0.17| 0.15| 0.20| SBERT DistilBERT sentence embeddings, class weights |
| 15   | 0.15| 0.33| 0.10| logistic regression, feature engineering             |
| 16   | 0.07| 0.04| 0.60| tree-based ensemble, LASER sentence embeddings, under-sampling |
| 4    | 0.00| 0.00| 0.00| camemBERT                                           |
| 29   | 0.00| 0.00| 0.00| NA                                                  |

Table 4: Task 2c (Russian) system summaries and F1-scores (F1), precision (P), and recall (R) for the “positive” class (i.e., tweets reporting an adverse effect of a medication).

| Team | F1  | P   | R   | System Summary                                      |
|------|-----|-----|-----|-----------------------------------------------------|
| 26   | 0.51| 0.45| 0.60| Conversational RuBERT, under-sampling, ensemble, RuDReC corpus |
| 25   | 0.51| 0.48| 0.70| EnRuDR-BERT, ensemble, bilingual training, RuDReC and PsyTAR corpora |
| 5    | 0.48| 0.36| 0.70| RuBERT                                             |
| 22   | 0.42| 0.35| 0.55| SBERT DistilBERT sentence embeddings, class weights |
| 4    | 0.36| 0.34| 0.40| RuBERT                                             |
| 28   | 0.36| 0.29| 0.46| NA                                                  |
| 16   | 0.35| 0.22| 0.89| SVM, LASER sentence embeddings, under-sampling      |

3.3 Task 3: Automatic Extraction and Normalization of Adverse Effects in English Tweets

Table 5 presents the F1-scores for the NER-based extraction of adverse effect text spans, and the precision, recall, and F1-scores for the normalization to the MedDRA ID, for each of the seven team’s best-performing systems for Task 3. Team 25 outperformed the other teams for all the presented performance metrics. For the NER-based extraction, they used a transformer-based architecture with domain-specific models, dictionary-based features, and additional training data from the CADEC corpus (Karimi et al., 2015). For normalization, they used a domain-specific, BERT-based classifier, additional training data, and similarity metrics comparing BERT-based word embeddings of Unified Medical Language System (UMLS) concepts and extracted NERs. Several other teams used similar approaches, so the performance of Team 26 might be attributed to their language models that were pre-trained specifically for detecting adverse drug reactions.

| Team | F1  | N   | F1  | N   | System Summary                                      |
|------|-----|-----|-----|-----|-----------------------------------------------------|
| 25   | 0.76| 0.46| 0.48| 0.44| EnDR-BERT, dictionary, BERT-based similarity metrics, CADEC |
| 2    | 0.73| 0.38| 0.34| 0.44| BERT, CADEC, SMM4H'17 corpus                        |
| 10   | 0.69| 0.35| 0.33| 0.38| RoBERTa, multi-task learning                        |
| 4    | 0.58| 0.22| 0.24| 0.20| SciBERT/BioBERT/BERT ensemble, fastText-based similarity metrics, CADEC |
| 1    | 0.46| 0.20| 0.35| 0.14| BiLSTM, CRF, GloVe and EXT word embeddings, QuickUMLS |
| 27   | 0.56| 0.15| 0.15| 0.14| NA                                                  |
| 16   | 0.16| 0.00| 0.00| 0.00| dictionary                                           |

3.4 Task 4: Automatic Characterization of Prescription Medication Abuse Chatter in Tweets

Table 6 presents the precision, recall, and F1-scores for the “potential abuse/misuse” class, for each team’s best-performing system for Task 4. Team 13 achieved the highest F1-score (0.51) using a CNN, fastText word embeddings, and data augmentation by means of manufacturing tweets that are semantically similar to the training data. This F1-score, however, is lower than the F1-score (0.67) of a stacked ensemble of BERT (Devlin et al., 2019), ALBERT (Lan et al., 2020), and RoBERTa models, presented in recent work (Ali Al-Garadi et al., 2020).

| Team | F1  | P   | R   | System Summary                                      |
|------|-----|-----|-----|-----------------------------------------------------|
| 13   | 0.51| 0.39| 0.50| CNN, fastText word embeddings, data augmentation     |
| 10   | 0.73| 0.38| 0.34| BERT, CADEC, SMM4H'17 corpus                        |
| 16   | 0.16| 0.00| 0.00| dictionary                                           |
Table 6: Task 4 system summaries and F₁-scores (F₁), precision (P), and recall (R) for the “potential abuse/misuse” class.

| Team | F₁   | P    | R    | System Summary                                                                 |
|------|------|------|------|--------------------------------------------------------------------------------|
| 13   | 0.51 | 0.53 | 0.50 | CNN, fastText word embeddings, data augmentation                              |
| 1    | 0.49 | 0.46 | 0.51 | SVM, under-sampling                                                            |
| 16   | 0.46 | 0.35 | 0.67 | SVM, sent2vec sentence and bi-gram embeddings pre-trained on tweets, under-sampling |

3.5 Task 5: Automatic Classification of Tweets Reporting a Birth Defect Pregnancy Outcome

Table 7 presents the micro-averaged precision, recall, and F₁-score for the “defect” and “possible defect” classes, for each team’s best-performing system. Teams 6 and 24 achieved the highest micro-averaged F₁-scores (0.69). While Team 6 achieved a higher micro-averaged recall (0.73) than Team 24 (0.67) using a hard-voting ensemble of nine BioBERT-based models, Team 24 achieved a higher micro-averaged precision (0.71) than Team 6 (0.65) using ELMo word embeddings and data-specific resources for modeling birth defects, pregnancy-related information, people’s names, and family relations. Team 19 also achieved a higher micro-averaged recall (0.69) than Team 24 (0.67) using BioBERT, but achieved a substantially lower micro-averaged precision (0.56) than Team 24 (0.71). Overall, for this imbalanced data, models based on contextualized word representations—BioBERT (Lee et al., 2020a) or ELMo (Peters et al., 2018)—outperformed a CNN-BiGRU neural network with GloVe word embeddings (Pennington et al., 2014). Recent work (Klein et al., 2019) presents baseline F₁-scores of an SVM classifier for the “defect” (0.65) and “possible defect” (0.51) classes.

| Team | F₁   | P    | R    | System Summary                                                                 |
|------|------|------|------|--------------------------------------------------------------------------------|
| 6    | 0.69 | 0.65 | 0.73 | BioBERT, data augmentation, ensemble                                           |
| 24   | 0.69 | 0.71 | 0.67 | ELMo, GCNN, ANNIE NER, medical and family relations lexicons                  |
| 19   | 0.62 | 0.56 | 0.69 | BioBERT pre-trained on tweets                                                 |
| 11   | 0.58 | 0.54 | 0.64 | GloVe word and hashtag embeddings pre-trained on tweets, CNN, BiGRU            |

Table 7: Task 5 system summaries and micro-averaged F₁-score (F₁), precision (P), and recall (R) for the “defect” and “possible defect” classes.

4 Conclusion

This paper presented an overview of the #SMM4H 2020 shared tasks. With 29 teams and a total of 130 system submissions, participation in the #SMM4H shared tasks continues to grow. All of the teams with the best-performing system for each task used deep learning-based systems, most of which were transformer-based architectures. The system description papers that are cited in Appendix A were each peer-reviewed by two reviewers and provide further details about 26 teams’ systems.

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### Appendix A. Team Numbers and System Description Papers

| Team | System Description Paper |
|------|--------------------------|
| 1    | (Vydiswaran et al., 2020) |
| 2    | (Gattepaille, 2020)      |
| 3    | (Casola and Lavelli, 2020) |
| 4    | (Saha et al., 2020)      |
| 5    | (Blinov and Avetisian, 2020) |
| 6    | (Bai and Zhou, 2020)     |
| 7    | (Khademi et al., 2020)   |
| 8    | (Dang et al., 2020)      |
| 9    | (Lichouri and Abbas, 2020) |
| 10   | (Kalyan and Sangeetha, 2020) |
| 11   | (Reddy, 2020)            |
| 12   | (Babu and Eswari, 2020)  |
| 13   | (Metzger et al., 2020)   |
| 14   | (Lee et al., 2020b)      |
| 15   | (Tanguy et al., 2020)    |
| 16   | (Liza, 2020)             |
| 17   | (Zhao et al., 2020)      |
| 18   | (Mehnaz, 2020)           |
| 19   | (Dima et al., 2020)      |
| 20   | (Mahendran et al., 2020) |
| 21   | (Wang et al., 2020)      |
| 22   | (Gencoglu, 2020)         |
| 23   | (Aduragba et al., 2020)  |
| 24   | (Bagherzadeh and Bergler, 2020) |
| 25   | (Miftahutdinova et al., 2020) |
| 26   | (Gusev et al., 2020)     |
| 27   | NA                       |
| 28   | NA                       |
| 29   | NA                       |