ABSTRACT

This paper provides an overview of the Arabic Sentiment Analysis Challenge organized by King Abdullah University of Science and Technology (KAUST). The task in this challenge is to develop machine learning models to classify a given tweet into one of the three categories Positive, Negative, or Neutral. From our recently released ASAD dataset, we provide the competitors with 55K tweets for training, and 20K tweets for validation, based on which the performance of participating teams are ranked on a leaderboard, https://www.kaggle.com/c/arabic-sentiment-analysis-2021-kaust. The competition received in total 1247 submissions from 74 teams (99 team members). The final winners are determined by another private set of 20K tweets that have the same distribution as the training and validation set. In this paper, we present the main findings in the competition and summarize the methods and tools used by the top ranked teams. The full dataset of 100K labeled tweets is also released for public usage, at https://www.kaggle.com/c/arabic-sentiment-analysis-2021-kaust/data.

Keywords Arabic Sentiment Analysis · Arabic Tweets · Deep Learning · Sentiment Analysis Competition

1 Introduction

Sentiment Analysis (SA) is a widely studied problem in Natural Language Processing (NLP). It is the task of automatically detecting and identifying the sentiment of a written text, usually by labeling a piece of text as Positive, Negative, or Neutral sentiment. In recent years, the growth of social media allows people to share their own ideas, thoughts, and emotions in public. In Twitter, for instance, users generate huge amounts of text data containing their insights [1]. Consequently, Sentiment Analysis of tweets becomes popular and has been studied for different purposes, from analyzing sentiments in general to specific fields. The specific fields include marketing analysis of services or products [2, 3], political field analysis [4, 1, 5], and public action towards events, persons, and recently, pandemics [6, 7, 8].

Arabic is one of the most popular languages in the world. It is the official language for 27 countries located in the Middle East and North Africa. Recently, Arabic natural language processing has attracted a lot of attention due to the increase usage of the language over the web and social media. Arabic exists in different forms and dialects according to each country or area. The formal form of Arabic is used in formal purposes like education and news [9]. However, in social media like Twitter, the informal and the free writing forms of the language are widely used and make the studies of Arabic tweets more complicated [10].

We launch an “Arabic Sentiment Analysis Competition” for promoting the study in this topic [11]. The task in this competition is to analyze the sentiments of Arabic tweets by classifying a given tweet text into one of the three categories Positive, Negative, or Neutral.
categories: Positive, Negative, or Neutral. The competition is sponsored by KAUST. The award to top-3 winners is 17000 USD in total. It runs on Kaggle\textsuperscript{2}, a popular platform for Machine Learning Competitions.

The competition is based on our released benchmark dataset ASAD \textsuperscript{11}, which is a large collection of 100K Arabic tweets, annotated for sentiment analysis tasks. We provided the competitors with training and testing files. The training file contains 55K annotated tweets, and the testing file (TEST1) contains 20K tweets, based on which the performance of participation teams is ranked on a leaderboard. Additionally, we kept another testing file (TEST2) of 20K tweets, which was not released to the competitors and used as a private testing file.

Seventy-four teams participated in this competition and in total made 1247 submissions. We summarize the techniques, methods, and tools used by the top-ranked teams in this paper. Basically, all the participants used some preprocessing techniques, such as removing the URLs, hashtags, user ids, foreign characters, and repeated characters. In general, all the top-ranked teams used the state-of-the-art (SOTA) pre-trained language model MARBERT to learn new representation of tweets. MARBERT \textsuperscript{12} is a large-scale Arabic pre-trained language model that focuses on both dialectal Arabic and modern standard Arabic. However, each team has its own approach for how to use MARBERT and other different deep learning techniques. Section 3 describes these approaches in details.

For determining the winners, we followed two steps. First, we ranked the teams by their performance on TEST1, as shown in the leaderboard. Second, we invited the top-ranked teams to submit their codes for the evaluation on TEST2, which has the same distribution as TEST1 and the training dataset. The final winners were determined based on the results of TEST2. More details can be found in Section 2 of the competition introduction.

The rest of this paper is organized as follows. Section 2 describes the competition task, the dataset, the evaluation process and baseline models. Section 3 discusses the participants’ results and the used models of the top three winning participants. Section 4 introduces other tasks with similar objective; i.e., Arabic sentiment analysis. Finally, Section 5 provides concluding remarks on KAUST 2021 Arabic sentiment analysis competition.

## 2 The Competition

The Arabic sentiment analysis competition is a multi-class classification task, where sentiment is identified at a 3-point scale. The goal is to classify the sentiment of a tweet as either: positive, negative or neutral. The competition was hosted on Kaggle framework and sponsored by KAUST. The prizes for the first three winners were 10000 USD, 5000 USD and 2000 USD, respectively.

### 2.1 Dataset Description

The competition is organized by using our ASDA dataset, which is the largest to this date for Arabic tweets sentiment analysis. It contains 100K tweets annotated as either positive, negative or neutral. The tweets in ASDA were collected in the period between May 2012 and April 2020. They are written in different Arabic dialects including Khaleeji, Hijazi, Egyptian and Modern Standard Arabic. Table 1 shows some examples of the annotated tweets from ASDA. The data collection and annotation were done by Lucidya\textsuperscript{3} which is an AI-based company with rich experience in organizing data annotation projects. A detailed description of our ASAD dataset and the process of collection and annotation can be found in \cite{11}. The distribution of the released data in competition can be found in Table 2.

The full ASDA dataset is available to the research community to be used freely beyond the competition. The dataset containing tweet IDs and annotations is available for free access\textsuperscript{4}. Additionally, to simplify the process of obtaining tweets from tweet IDs, we provide a platform in which users can supply tweet IDs and get the actual tweet content in return. To get access to this platform, users can register in the competition’s website\textsuperscript{5} and freely use the online platform.

### 2.2 Participation Teams

At the time of writing, a total of 764 users registered in the competition’s website, from 45 different countries. Figure 1a illustrates the number of registered users per country for the top five countries. We can see that most registered users came from Saudi Arabia, followed by Algeria then Egypt. Figure 1b visualizes the number of downloaded tweets, using the platform, per month. From the figure, we can conclude that the largest number of tweets were downloaded in January. Tweets continued to be downloaded using the platform through the months from February to June, 2021.

\textsuperscript{2}https://www.kaggle.com/c/arabic-sentiment-analysis-2021-kaust
\textsuperscript{3}https://lucidya.com/
\textsuperscript{4}https://www.kaggle.com/c/arabic-sentiment-analysis-2021-kaust/data
\textsuperscript{5}https://wti.kaust.edu.sa/solve/Arabic-Sentiment-Analysis-Challenge
Table 1: Example of tweets in ASAD

| Tweet | Sentiment |
|-------|-----------|
| لأول مرة أفرج بدرجته في الكلب الفارس الذي أنا فيها دي في الحمد لله الحمد له بجد ؟؟ | Positive |
| أحس بان مصر ستكون في الأيام القادمة أكثر اشراقا وأكثر قوة | Positive |
| شعرة أخرى بريعة عارمة في السفري عن كل شيء. | Negative |
| هو أنا كا كدا عمان بكشف في ناس وحشي منه | Negative |
| السلام عليك .. كي يوم تأخذ نتيجة فيروس كورونا ؟ | Neutral |
| القوة ليست دائما فيما نقول ونفعل أحيانا تكون فيما نصمت عنه ، فيما نتركه باردتنا ، فيما نتجاهلها. | Neutral |

Table 2: Class distribution in data splits in competition. The All set represents the complete competition dataset. TRAINING, TEST1 and TEST2 are the three splits used in the competition and also in the benchmark models evaluation. The three splits maintained the same class distribution as the original complete dataset.

|          | TRAINING | TEST1 | TEST2 | All    |
|----------|----------|-------|-------|--------|
|          | No. tweets (%) | No. tweets (%) | No. tweets (%) | No. tweets (%) |
| Positive | 8821     | 0.16  | 3150  | 0.16   | 3244    | 0.16   | 15215  | 0.16  |
| Negative | 8820     | 0.16  | 3252  | 0.16   | 3195    | 0.16   | 15267  | 0.16  |
| Neutral  | 37359    | 0.68  | 13598 | 0.68   | 13561   | 0.68   | 64518  | 0.68  |
| Total    | 55000    | 1.00  | 20000 | 1.00   | 20000   | 1.00   | 95000  | 1.00  |

(a) Distribution of registered users per country, for the top five countries. (b) Distribution of downloaded tweets per month, from January to June, 2021. (c) Distribution of participation team sizes.

Figure 1: Statistics of registration and participation teams.

2.3 Evaluation Metrics and Baselines

For the multi-class sentiment analysis, we used the Macro-F1 score as the official evaluation metric. Evaluation was done in two phases: In phase I, we considered the results of TEST1 ranked by Macro-F1 in Kaggle’s leaderboard. Then, in phase II, we invited the top-ranked teams to submit their codes for the evaluation on TEST2. With the submitted codes, we first checked the codes and verified the submitted results of TEST1. Then, we did the final evaluation on TEST2. The final winners were determined based on the Macro-F1 scores of TEST2.

We run several baseline models in [11]. The best model is based on AraBERT [13], which achieved an Macro-F1 score of 0.68 on both TEST1 and TEST2. We were expecting the winners to achieve much higher Macro-F1 scores than 0.68.

3 The Winning Teams

Seventy-four teams participated in this challenge, with a total of 1,247 submissions. The majority of teams (81%) consisted of one member only, and the remaining groups had 2-5 members. Figure 1c illustrates the distribution of team sizes for all participating teams. Table 3 lists the leaderboard from Kaggle, which ranks all teams by their Macro-F1 score on TEST1. Table 4 shows the performance of the top 20 teams on TEST1 in terms of accuracy, precision, recall, Micro-F1, Macro-F1, and weighted-F1 scores.
Table 3: Results achieved by all teams. Teams are ordered by the main evaluation metric, Macro-F1.

| ID | Team Name          | Score | ID | Team Name          | Score | ID | Team Name             | Score |
|----|--------------------|-------|----|--------------------|-------|----|-----------------------|-------|
| 1  | GOP                | 0.79986 | 26 | DGGGL              | 0.73666 | 51 | Catherine Horbach     | 0.65959 |
| 2  | Ahmed Elbehiry     | 0.79797 | 27 | [Deleted]          | 0.73601 | 52 | Hussein Ghaly         | 0.65446 |
| 3  | Wissam Antoun      | 0.7962  | 28 | Vision-AJ          | 0.73337 | 53 | shimaa                | 0.6511  |
| 4  | CS-UM6P            | 0.79461 | 31 | Amal               | 0.72891 | 54 | alashraflover14       | 0.64493 |
| 5  | Ali Salhi          | 0.79349 | 30 | Alkalhafa          | 0.72701 | 55 | Al_Salah              | 0.64112 |
| 6  | Taicheng Guo       | 0.79097 | 32 | Vadim Yermakov     | 0.72439 | 57 | Uliana Kobzar         | 0.62815 |
| 7  | [Deleted]          | 0.79099 | 33 | Abdulshahed Alqunber | 0.72294 | 58 | PSFA Team             | 0.627   |
| 8  | Salma Jamal        | 0.79099 | 34 | faiz faiz          | 0.72097 | 59 | OMA                   | 0.62411 |
| 9  | Abdullah I. Alharbi| 0.79014 | 35 | Jana Muhammad      | 0.71852 | 60 | Egor Gavrilenko       | 0.61251 |
| 10 | Aggies             | 0.78753 | 36 | Abdullah Hussein   | 0.71503 | 61 | Iaouni MAH-MOUIDI     | 0.60329 |
| 11 | KUIS AI            | 0.78735 | 37 | adamHesham         | 0.71097 | 62 | dream                 | 0.58882 |
| 12 | AraBrain Hidden Layers | 0.78482 | 38 | Engma              | 0.70668 | 63 | Shahad Althobaiti     | 0.58322 |
| 13 | AEM                | 0.77837 | 39 | Horizon            | 0.70238 | 64 | Mohammed Salem        | 0.57911 |
| 14 | Omar Mohamed       | 0.77455 | 40 | Mikita Daroshkin   | 0.69881 | 65 | Mazin Taha            | 0.57353 |
| 15 | EAM                | 0.77248 | 41 | Yousef Nafea       | 0.69564 | 66 | Nour samia            | 0.50982 |
| 16 | NLP players        | 0.77074 | 42 | cher zola          | 0.69491 | 67 | Hassan                 | 0.32578 |
| 17 | raghad             | 0.7691  | 43 | nemo               | 0.68915 | 68 | ArabicNLP             | 0.32353 |
| 18 | Muradha Aljubran   | 0.76004 | 44 | Vladimir           | 0.68854 | 69 | Khaled Al-Shamaa       | 0.31951 |
| 19 | Roobaa Alroobaa    | 0.7605  | 45 | Francois de Ryckel | 0.68738 | 70 | Abdulalah             | 0.30239 |
| 20 | Yolo               | 0.75998 | 46 | Manal Mohammed     | 0.68731 | 71 | Yuchen Li             | 0.29423 |
| 21 | Marwa Gharbi       | 0.75917 | 47 | Maxim Zherelo      | 0.68194 | 72 | Mays AbuSalah         | 0.28201 |
| 22 | Husain Khutba      | 0.7548  | 48 | Kolosov Arseny     | 0.67784 | 73 | ...                   | 0.26981 |
| 23 | X4N7H055           | 0.75271 | 49 | Vad Osipenko       | 0.66425 | 74 | noreddine belhadjecheikh | 0.09071 |
| 24 | Hadjer             | 0.75026 | 50 | dtr1               | 0.66239 | 75 | ...                   | 0.09071 |

The competition requests the top ranked teams to submit their codes at the end of the competition for final evaluation. Failure to do so results in the exclusion from the final evaluation. Six out of ten teams have submitted their codes. We verified their results of TEST1. Then, we did the final evaluation on TEST2. The reason for using TEST2 is to assess the models with a completely new set that was never seen by the model or the competitors. The performance of a model on TEST2 should be as good as on TEST 1.

Table 5 shows the results of TEST2 for the top-ranked teams. It can be observed that all the participating models outperformed the baseline results, as the baselines used very simple and basic methods. The top three best-performing teams were Wissam Antoun at first place with Macro-F1 = 0.79249. Both Abdullah I. Alharbi and Ali Salhi came in the second place since their Macro-F1 is about 0.79039. The CS-UM6P team came at third place with Macro-F1 = 0.78961.

Generally, all the top three ranked teams used MARBERT to get tweets representation. MARBERT [12] is a large-scale Arabic pre-trained model that focuses on both dialectal Arabic and modern standard Arabic. MARBERT is pre-trained over 6 Billions Arabic tweets. The teams followed similar steps for text pre-processing, such as:

- Removing unrecognizable symbols or characters that are not useful in understanding the text meaning; for instance, stop words, punctuation marks, diacritics, and elongations (taweez).
- Replacing extra content in tweets with special tokens. For example “HASH” for hashtags, “USER” for user mentions, and “URL” for links.
- For emojis, the teams retained them as they are useful in emotion and sentiment analysis tasks. They also placed whitespace between any emojis to separate them and ensure they will be treated as separate words.

However, each team has its own approach for how to use MARBERT and other different deep learning techniques. Below, we provide a brief description of their approaches.

### 3.1 First Place Winner: Wissam Antoun Approach

This solution is based on an ensemble of 5 models with varying preprocessing and classifier design. All model variants are built over MARBERT. For classifier design, all models use a dense layer on top of MARBERT unless otherwise

The competition requests the top ranked teams to submit their codes at the end of the competition for final evaluation. Failure to do so results in the exclusion from the final evaluation. Six out of ten teams have submitted their codes. We verified their results of TEST1. Then, we did the final evaluation on TEST2. The reason for using TEST2 is to assess

Table 5 shows the results of TEST2 for the top-ranked teams. It can be observed that all the participating models outperformed the baseline results, as the baselines used very simple and basic methods. The top three best-performing teams were Wissam Antoun at first place with Macro-F1 = 0.79249. Both Abdullah I. Alharbi and Ali Salhi came in the second place since their Macro-F1 is about 0.79039. The CS-UM6P team came at third place with Macro-F1 = 0.78961.

Generally, all the top three ranked teams used MARBERT to get tweets representation. MARBERT [12] is a large-scale Arabic pre-trained model that focuses on both dialectal Arabic and modern standard Arabic. MARBERT is pre-trained over 6 Billions Arabic tweets. The teams followed similar steps for text pre-processing, such as:

- Removing unrecognizable symbols or characters that are not useful in understanding the text meaning; for instance, stop words, punctuation marks, diacritics, and elongations (taweez).
- Replacing extra content in tweets with special tokens. For example “HASH” for hashtags, “USER” for user mentions, and “URL” for links.
- For emojis, the teams retained them as they are useful in emotion and sentiment analysis tasks. They also placed whitespace between any emojis to separate them and ensure they will be treated as separate words.

However, each team has its own approach for how to use MARBERT and other different deep learning techniques. Below, we provide a brief description of their approaches.

### 3.1 First Place Winner: Wissam Antoun Approach

This solution is based on an ensemble of 5 models with varying preprocessing and classifier design. All model variants are built over MARBERT. For classifier design, all models use a dense layer on top of MARBERT unless otherwise
Table 4: Other Metrics on official (Kaggle) results of the top 20 teams on TEST1 ranked by Macro-F1

| Team              | Acc    | Precision | Recall | Micro-F1 | Macro-F1 | Weighted-F1 |
|-------------------|--------|-----------|--------|----------|----------|-------------|
| GOF               | 0.84945 | 0.80324   | 0.79656 | 0.84945  | 0.79985  | 0.84907     |
| Ahmed Elbehiry    | 0.84940 | 0.80342   | 0.79630 | 0.84940  | 0.79979  | 0.84900     |
| Wissam Antoun     | 0.84595 | 0.79868   | 0.79399 | 0.84595  | 0.79620  | 0.84581     |
| Ali Salhi         | 0.84455 | 0.79848   | 0.79407 | 0.84455  | 0.79439  | 0.84399     |
| Taicheng Guo      | 0.84280 | 0.79614   | 0.78625 | 0.84280  | 0.79097  | 0.84233     |
| Salma Jamal       | 0.84165 | 0.79100   | 0.79093 | 0.84165  | 0.79090  | 0.84178     |
| Abdullah I. Alharbi | 0.83955 | 0.78802   | 0.79327 | 0.83955  | 0.79014  | 0.84033     |
| Aggies            | 0.84060 | 0.79389   | 0.78237 | 0.84060  | 0.78753  | 0.84021     |
| KUIS AI           | 0.84250 | 0.80158   | 0.77533 | 0.84250  | 0.78735  | 0.84105     |
| AraBrain Hidden Layers | 0.83820 | 0.78969   | 0.78123 | 0.83820  | 0.78482  | 0.83793     |
| AEM               | 0.84000 | 0.80833   | 0.75453 | 0.84000  | 0.77837  | 0.83633     |
| Omar Mohamed      | 0.82110 | 0.75697   | 0.79797 | 0.82110  | 0.77455  | 0.82481     |
| EAM               | 0.83215 | 0.78413   | 0.76197 | 0.83215  | 0.77248  | 0.83041     |
| NLP players       | 0.82425 | 0.76740   | 0.77468 | 0.82425  | 0.77074  | 0.82509     |
| Raghad            | 0.83080 | 0.78403   | 0.75604 | 0.83080  | 0.76910  | 0.82555     |
| Murtada Aljunban  | 0.82960 | 0.78083   | 0.75479 | 0.82960  | 0.76704  | 0.82757     |
| Roobaca Alroobaea | 0.82230 | 0.77044   | 0.75145 | 0.82230  | 0.76050  | 0.82089     |
| Yolo              | 0.81815 | 0.75919   | 0.76122 | 0.81815  | 0.75998  | 0.81871     |
| Marwa Gharbi      | 0.82950 | 0.79645   | 0.73114 | 0.82950  | 0.75917  | 0.82425     |

Table 5: Final evaluation for top-ranked teams on TEST2

| Team              | Acc    | Precision | Recall | Micro-F1 | Macro-F1 | Weighted-F1 |
|-------------------|--------|-----------|--------|----------|----------|-------------|
| Wissam Antoun     | 0.84510 | 0.80669   | 0.78068 | 0.84510  | 0.79249  | 0.84382     |
| Abdullah I. Alharbi | 0.83975 | 0.79222   | 0.79017 | 0.83975  | 0.79039  | 0.84011     |
| Ali Salhi         | 0.84301 | 0.80037   | 0.78158 | 0.84301  | 0.79039  | 0.84001     |
| CS-UM6P           | 0.84520 | 0.81042   | 0.77198 | 0.84520  | 0.78961  | 0.84279     |
| Taicheng Guo      | 0.81720 | 0.76040   | 0.75694 | 0.81720  | 0.75770  | 0.81743     |
| AraBrain Hidden Layers | 0.79275 | 0.78351   | 0.63320 | 0.79275  | 0.68273  | 0.77599     |

specified. Model training is done by hyperparameter grid-search with 5-fold cross-validation. Model I is a vanilla variant with only the general preprocessing steps applied. Model II enhances the emoji representation by replacing OOV emojis with ones that have a similar meaning.

The participant noticed the repetitive use of "سلام عليكم" and "ورحمة الله وبركاته" in neutral tweets. This could confuse the classifier, if it encountered these words in for example a negative tweet, hence in Model III the variation of the phrase mentioned is removed before using fuzzy matching algorithms. In Model IV, the team tried to help the model by appending a sarcasm label to the input. They first trained a separate MARBERT on the ArSarcasm [14] dataset and then used it to label the training and test sets. Model V uses the vanilla preprocessing approach, but instead of a dense layer built on top of MARBERT, the team follows the approach detailed by Safaya et.al. [15] which uses a CNN-based classifier instead.

For the final prediction, the average prediction is computed from the predictions of the 5 models from cross-validation (this is done for each model separately). The participants noticed that the distribution of the predicted sentiment classes, doesn’t quite match the true distribution, this is due to the model preferring the neutral class over the positive class. To counter that, they apply what they call Label-Weighted average, where after the final averaging they rescale each score of the three labels with a weight. The three weights were determined empirically.

3.2 Second Place Winner (I): Abdullah I. Alharbi Approach

The proposed method incorporates static character and word embeddings (CE and WE) and contextualized embeddings (MARBERT) to obtain a good representation for tweets. For static character and word embeddings, the team utilized ACWE model that was produced by [16]. ACWE combines static character- and word-level models to take advantage of each one of them. The word-level model was pre-trained on a large-scale dataset that consists of tweets written in a variety of Arabic dialects. It was constructed through the use of the word2vec algorithm as a means of learning how various individual words were represented. The character-level model is a pre-trained character representation model (CE) [17] that has been successfully employed in different Arabic affect tasks.
After ACWE model, CNN-LSTM architecture was employed as proposed in [18] to obtain the embeddings vectors after the training process. For generating contextual embeddings, the team also fine-tuned MARBERT model with the training data. Therefore, they concatenated both obtained vectors and fed it to a dense layer of number-of-classes output was put in place by leveraging softmax. Figure 2 illustrates the architecture of the proposed model.

3.3 Second Place Winner (II): Ali Salhi Approach

This solution is based on fine-tuning MARBERT with the training data by using different splitting ratios and training hyper parameters to get good performance. But the key factors in providing the high-performance model with steady results were the appending stems process and the feedback approach conducted on the training data.

Appending stems was implemented as an additional step for the data cleaning process. For each tweet, the stems of its words are extracted and added to it as extra text. The feedback approach was used to extend the training data by tweets from the test data. This was done by repeating the training with different N learning rates. Then, for a given test tweet, if the predicted labels in the N training trials are equals, the test tweet with its stable label will be added to the training data as an extra instance.

3.4 Third Place Winner: CS-UM6P Approach

The team proposed a deep multi-task model based on MARBERT encoder and task specific-attention layers [19, 20, 21]. In addition to the multi-class classification task, they have employed a one-versus-all (binary classification) task for each sentiment. To extract the task’s discriminative features, they utilized four task attention layers on top of MARBERT’s tokens embeddings. Each task’s classifier is fed the output of its specific attention layer and the pooled output of MARBERT encoder. At the inference, the logits of binary tasks are concatenated and added to the logits of the multi-class classification to compute the probabilities of each polarity.

4 Related Work

Shared tasks allow the research community to work simultaneously towards solving a challenging problem. Shared tasks specify the main problem to be solved, and provide the research community with datasets, which are often challenging to obtain. Two similar shared tasks were organized in the past five years: SemEval 2017 - Task 4 [22], and WANLP 2021 - Subtask 2 [23]. Description of each shared task is provided next, and summary of the released datasets is provided in Table 6.

SemEval 2017 - Task 4. In 2017, SemEval announced a shared task which included Arabic dataset for the first time. Specifically, subtask A under SemEval-2017 Task 4 [22] released a dataset with a total of 9K Arabic tweets, divided into 35% for training and 65% for testing. Each tweet was labeled as either positive, negative or neutral. The distribution of positive/negative/neutral tweets in the training set is 22%/34%/44%, respectively, and 25%/36%/39% in the testing set. The shared task has several subtasks, including overall sentiment analysis on a 2-point scale and a 3-point scale, as well as topic-level sentiment. A total of 8 teams participated in the Arabic subtask A, where the winning team used Naive Bayes classifier with a combination of lexical and sentiment features.

WANLP 2021 - Subtask 2. In 2021, a shared task was organized by the sixth Workshop on Arabic Natural Language Processing (WANLP) on sentiment detection in Arabic [23]. The shared task had two subtasks: sarcasm detection (subtask 1) and sentiment analysis (subtask 2). The dataset released for this shared task was ArcSarcasm-v2 [14], which has a total of 15K tweets divided into 80% training and 20% testing. The sentiment of each tweet was labelled as either positive, negative or neutral. The distribution of the positive/negative/neutral tweets in the training set is 17%/37%/46%, respectively, and 19%/56%/25% in the testing set. Additional labels were provided including sarcasm and dialect.
Table 6: Comparison of released datasets from similar tasks. Values indicate the number of tweets and percentage for each label in the training, testing and complete datasets, respectively.

|                      | SemEval 2017 (Task 4) | WANLP 2021 (subtask 2) |
|----------------------|------------------------|------------------------|
|                      | Training | Testing | Total | Training | Testing | Total |
| Positive             | 743 (22%) | 1,514 (25%) | 2,257 (24%) | 2,180 (17%) | 575 (19%) | 2,755 (18%) |
| Negative             | 1,142 (34%) | 2,364 (39%) | 3,506 (37%) | 4,621 (37%) | 1,677 (56%) | 6,298 (41%) |
| Neutral              | 1,470 (44%) | 2,222 (36%) | 3,692 (39%) | 5,747 (46%) | 748 (25%) | 6,495 (41%) |
| Total                | 3,355 (100%) | 6,100 (100%) | 9,455 (100%) | 12,548 (100%) | 3,000 (100%) | 15,548 (100%) |

Though the objective of both shared tasks is similar to KAUST’s 2021 Arabic sentiment analysis competition, the size of the datasets released varies significantly. The dataset released in our competition, i.e., ASAD [11], is almost six times larger than ArcSarcasm-v2 [14] and ten times larger than SemEval 2017 Arabic sentiment analysis dataset [22].

5 Conclusion

We have described the data, evaluation process, and the results of “Arabic Sentiment Analysis Competition” organized by KAUST. The task is to analyze the sentiment of Arabic tweets by performing sentiment analysis classification. We received a high number of submissions, in total 1247 submission by 74 teams. Overall, the best systems used several preprocessing steps and they used the state-of-the-art pre-trained models such as MARBERT as well as different deep learning techniques. The final evaluation depends on the Macro-F1 results of a private testing file. The first-place winner has obtained 0.79249, and two participances shared the second place with Macro-F1=0.79039, and the third winner obtained 0.78961. We have made our annotated dataset ASAD publicly available to the research community beyond the competition. In addition to its main usage in the sentiment analysis, the dataset can be also used for other NLP tasks such as, dialect identification and spam detection. We will update the dataset with more annotations later.

Acknowledgments

We would like to thank KAUST for sponsoring this competition. A great thank to the member of the host team Mohammad Al-Barazi. We also thank the winners: Wissam Antoun, Abdullah Alharbi, Ali Salhi, and Abdellah Elmekki for their kind help in describing their models. Finally, we thank Hassan Alzahrani, Arsalan Khatri, and Sarah Mitha for the IT support.

References

[1] Mohd Zeeshan Ansari, M.B. Aziz, M.O. Siddiqui, H. Mehra, and K.P. Singh. Analysis of political sentiment orientations on twitter. Procedia Computer Science, 167:1821–1828, 2020. International Conference on Computational Intelligence and Data Science.

[2] Nur Vidya, Mohamad Ivan Fanany, and Indra Budi. Twitter sentiment to analyze net brand reputation of mobile phone providers. Procedia Computer Science, 72:519–526, 2015. The Third Information Systems International Conference 2015.

[3] Sonia Anastasia and Indra Budi. Twitter sentiment analysis of online transportation service providers. In 2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS), pages 359–365, 2016.

[4] Akshat Bakliwal, Jennifer Foster, Jennifer van der Puil, Ron O’Brien, Lamia Tounsi, and Mark Hughes. Sentiment analysis of political tweets: Towards an accurate classifier. In Proceedings of the Workshop on Language Analysis in Social Media, pages 49–58, Atlanta, Georgia, June 2013. Association for Computational Linguistics.

[5] Jyoti Ramteke, Samarth Shah, Darshan Godhia, and Aadil Shaikh. Election result prediction using twitter sentiment analysis. In 2016 International Conference on Inventive Computation Technologies (ICICT), volume 1, pages 1–5, 2016.

[6] Ravikumar Patel and Kalpdrum Passi. Sentiment analysis on twitter data of world cup soccer tournament using machine learning. IoT, 1(2):218–239, 2020.

[7] Qiang Yang, Hind Alamro, Somayah Albaradei, Adil Salhi, Xiaoting Lv, Changsheng Ma, Manal Alshehri, Inji Jaber, Faroug Tifraten, Wei Wang, Takashi Gojobori, Carlos M. Duarte, Xin Gao, and Xiangliang Zhang.
SenWave: Monitoring the global sentiments under the covid-19 pandemic. arXiv preprint arXiv:2006.10842, 2020.

[8] Xiangliang Zhang, Qiang Yang, Somayah Albaradei, Xiaoting Lyu, Hind Alamro, Adil Salhi, Changsheng Ma, Manal Alshehri, I. Jaber, Faroug Tifratene, Wei Wang, T. Gojobori, C. Duarte, and Xin Gao. Rise and fall of the global conversation and shifting sentiments during the covid-19 pandemic. Humanities and Social Sciences Communications, 8:1–10, 2021.

[9] Ayah Zirikly and Mona Diab. In Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing, pages 176–185, 01 2015.

[10] Oumaima Oueslati, Erik Cambria, Moez Ben HajHmida, and Habib Ounelli. A review of sentiment analysis research in arabic language. Future Generation Computer Systems, 112:408–430, 2020.

[11] Basma Alharbi, Hind Alamro, Manal Alshehri, Zuhair Khayyat, Manal Kalkatawi, Inji Ibrahim Jaber, and Xiangliang Zhang. ASAD: A twitter-based benchmark arabic sentiment analysis dataset. arXiv preprint arXiv:2011.00578, 2021.

[12] Muhammad Abdul-Mageed, AbdelRahim Elmadany, and El Moatez Billah Nagoudi. ARBERT & MARBERT: Deep bidirectional transformers for Arabic. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 7088–7105, Online, August 2021. Association for Computational Linguistics.

[13] Wissam Antoun, Fady Baly, and Hazem Hajj. AraBERT: Transformer-based model for arabic language understanding, 2020.

[14] Ibrahim Abu Farha and Walid Magdy. From arabic sentiment analysis to sarcasm detection: The asarsarcasm dataset. In Proceedings of the 4th Workshop on Open-Source Arabic Corpora and Processing Tools, with a Shared Task on Offensive Language Detection, pages 32–39, 2020.

[15] Ali Safaya, Moutsam Abdellatif, and Deniz Yuret. KUISAIL at SemEval-2020 task 12: BERT-CNN for offensive speech identification in social media. In Proceedings of the Fourteenth Workshop on Semantic Evaluation, pages 2054–2059, Barcelona (online), December 2020. International Committee for Computational Linguistics.

[16] Abdullah I Alharbi, Phillip Smith, and Mark Lee. Enhancing contextualised language models with static character and word embeddings for emotional intensity and sentiment strength detection in arabic tweets. Procedia Computer Science, 189:258–265, 2021.

[17] Abdullah I Alharbi and Mark Lee. Combining character and word embeddings for affect in arabic informal social media microblogs. In International Conference on Applications of Natural Language to Information Systems, pages 213–224. Springer, 2020.

[18] Xingyou Wang, Weijie Jiang, and Zhiyong Luo. Combination of convolutional and recurrent neural network for sentiment analysis of short texts. In Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pages 2428–2437, 2016.

[19] Abdelkader El Mahdaouy, Abdellah El Mekki, Kabil Essefar, Nabil El Mamoun, Ismail Berrada, and Ahmed Khoumsi. Deep multi-task model for sarcasm detection and sentiment analysis in arabic language. In Proceedings of the Sixth Arabic Natural Language Processing Workshop, pages 334–339, 2021.

[20] Abdellah El Mekki, Abdelkader El Mahdaouy, Kabil Essefar, Nabil El Mamoun, Ismail Berrada, and Ahmed Khoumsi. Bert-based multi-task model for country and province level msa and dialectal arabic identification. In Proceedings of the Sixth Arabic Natural Language Processing Workshop, pages 271–275, 2021.

[21] Kabil Essefar, Abdellah El Mekki, Abdelkader El Mahdaouy, Nabil El Mamoun, and Ismail Berrada. Cs-um6p at semeval-2021 task 7: Deep multi-task learning model for detecting and rating humor and offense. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, 2021.

[22] Sara Rosenthal, Noura Farra, and Preslav Nakov. Semeval-2017 task 4: Sentiment analysis in twitter. In Proceedings of the 11th international workshop on semantic evaluation (SemEval-2017), pages 502–518, 2017.

[23] Ibrahim Abu Farha, Wajdi Zaghouani, and Walid Magdy. Overview of the wanlp 2021 shared task on sarcasm and sentiment detection in arabic. In Proceedings of the Sixth Arabic Natural Language Processing Workshop, pages 296–305, 2021.