Arabic Offensive Language Detection Using Machine Learning and Ensemble Machine Learning Approaches

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Abstract
Ensemble machine learning is a meta-learning machine learning method that aims to improve single learner classifier’s performance by combining predictions from multiple single learner classifiers. This study aims at investigating the effect of applying single learner machine learning approach and ensemble machine learning approach for offensive language detection on Arabic language. Classifying Arabic social media text is a very challenging task due to the ambiguity and informality of the written format of the text. Arabic language has multiple dialects with diverse vocabularies and structures, which increase the complexity of obtaining high classification performance. Our study shows significant impact for applying ensemble machine learning approach over the single learner machine learning approach. Among the trained ensemble machine learning classifiers, bagging performs the best in offensive language detection with F1 score of 88%, which exceeds the score obtained by the best single learner classifier by 6%. Our findings highlight the great opportunities of investing more efforts in promoting the ensemble machine learning approach solutions for offensive language detection models.

Keywords: text classification, Arabic NLP, offensive language

1. Introduction
The increasing number of online platforms for user generated content enables more people to experience freedom of expression than ever before. In addition, users of these platforms have the option of being anonymous and hiding their personal identity, which can increase the chance of misusing these technical features. Using offensive language has become one of the most common problems on social networking platforms. Text that contains some form of abusive behavior exhibiting actions with the intention of harming others is known as offensive language. Offensive language on social networking platforms can take multiple forms. Hate speech, aggressive content, cyberbullying, and toxic comments are different forms of offensive contents (Schmidt & Wiegand, 2017).

Reviewing the previous research on online offensive language detection, we find limited research covering Arabic language (Abdelfatah, Terjeanu, & Alhelbawy (2017); Abozinadah, Mbaziria, & Jones (2015); Alakrot, Murray, & Nikolov, 2018; Albadi, Kurdi, & Mishra, 2018, 2019a; Haidar, Chamoun, & Serhrouchni, 2017, 2018, 2019; Johnston & Weiss, 2017; Kaati et al., 2015; Magdy, Darwish, & Weber, 2015; Mohaouchane, Mourhir, & Nikolov, 2019; Mubarak, Darwish, & Magdy, 2017). Furthermore, most of the literature has limitations and their scopes are not covering the topic of offensive language detection on a comprehensive basis. For example, Alakrot, Murray, and Nikolov (2018) focuses on offensive and abusive language in Arabic comments in You Tube, but their analysis depends on a very small dataset of 1,100 comments, which is not enough to generalize their findings. Another example, studies from Albadi, Kurdi, and Mishra (2018, 2019a) are very specific in scope for religious hate speech only in Arabic Twitter content. The majority of NLP researchers explore methods and techniques for automatic detection of offensive language in English text that cannot be generalized to Arabic and other languages that have different structures and rules from the English language.

Detecting offensive language for Arabic contents is a complex task. It has multiple challenges including: a) the informal language used in posts of social media which are usually written using short forms and slangs that are difficult to semantically process and understand by the classifier; b) The variation and diversity of the Arabic language dialects and forms that add difficulties to the task of identifying offensive contents as the texts might need to go through multiple preprocessing steps before feeding it into the classification model. To address the problem of informal language, we preprocess each tweet by converting emoticons and emojis to an Arabic textual description of its contents and segmenting hashtags into space separated words. The variation of Arabic dialects is addressed by converting dialectal Arabic to Modern Standard Arabic (MSA). The classifiers we experiment with include: machine learning models such as Support Vector Machine (SVM), logistic regression, and decision tree; ensemble machine learning models such as bagging, AdaBoosts, and random forest. We explore word-level features and character-level features.
In the rest of this paper, we organize the content as follows: section 2 discusses related work of Arabic offensive language detection on social media; section 3 introduces data description, details of preprocessing, and the methodology of our models; experimental results are discussed in section 4. We also present the conclusion of our work at the end of the paper.

2. Related Work

There are few studies that focus on detecting offensive Arabic tweets for identifying abusive Twitter accounts (Abozinadah, Mbaziira, and Jones, 2015; Abozinadah and ones, 2017; Abozinadah, 2017). Abozinadah, Mbaziira, and Jones (2015) construct an initial dataset starting from 500 Twitter accounts based on a set of Arabic swear words. Then, they check the most recent 50 tweets, profile pictures, and hashtags for each of these 500 Twitter accounts to reach a dataset of 350,000 Twitter accounts and 1,300,000 tweets with balanced classes, half labelled abusive and the other half labelled non-abusive. They use three types of features including profile-based features, tweet-based features, and social graph features to train three classifiers; Naïve Bayes (NB), SVM, and Decision Tree (J48). Results show that the NB outperforms the other classifiers when used with 100 features and 10 tweets for each account with an accuracy score of 85% (Abozinadah, Mbaziira, and Jones, 2015; Abozinadah, 2017).

Arabic language has been studied also by Alakrot, Murray, and Nikolov (2018a, 2018b) for automatic detection of offensive language. They construct a dataset from YouTube comments based on selecting channels that has controversial videos about celebrities. Their final dataset includes 167,549 comments posted by 84,354 users, and 87,388 replies posted by 24,039 users from 150 YouTube datasets and skip. Abozinadah and ones, 2017). Abozinadah, Mbaziira, and Jones (2015) construct an initial dataset starting from 500 Twitter accounts based on a set of Arabic swear words. They then check the most recent 50 tweets, profile pictures, and hashtags for each of these 500 Twitter accounts to reach a dataset of 350,000 Twitter accounts and 1,300,000 tweets with balanced classes, half labelled abusive and the other half labelled non-abusive. They use three types of features including profile-based features, tweet-based features, and social graph features to train three classifiers; Naïve Bayes (NB), SVM, and Decision Tree (J48). Results show that the NB outperforms the other classifiers when used with 100 features and 10 tweets for each account with an accuracy score of 85% (Abozinadah, Mbaziira, and Jones, 2015; Abozinadah, 2017).

Mohauouchane, Mourhir, and Nikolov (2018a) explore multiple deep learning models to classify offensive Arabic language for YouTube comments using the same dataset developed by Alakrot, Murray, and Nikolov (2018a). They create word embedding using AraVec, which is trained on Twitter dataset and skip-gram model. Four deep learning models were evaluated for classifying offensive comments including convolutional neural network (CNN), Bidirectional Long short-term memory (Bi-LSTM), Bi-LSTM with attention mechanism, and combined CNN and LSTM. Results demonstrate an overall better performance for CNN with highest accuracy score of 87.84%, precision score of 86.10%, and F1 score of 84.05%, while the combined CNN-LSTM model shows better recall score of 83.46% (Mohauouchane, Mourhir, and Nikolov, 2019).

Ensemble machine learning methods have been applied to some applications of Arabic offensive language detection, such as cyberbullying. Haidar, Chamoun, and Serhrouchni (2017, 2019) use a dataset of 31,891 unbullying tweets and 2,999 bullying tweets manually labeled using two classes, ‘bull’ for bullying instances and ‘None’ for other instances. An algorithm for generating word embedding was used to create features. They investigate cyberbullying detection in two studies; one using single learner machine learning methods and another one using ensemble machine learning methods. The Naïve Bayes and the SVM classifiers were used in the machine learning single learner study. On the ensemble machine learning study, three models were explored: 1) stacking with simple linear regression as the meta-learning mechanism and classifiers include random forest, SVM, K-nearest neighbor, Bayesian logistic regression, and stochastic gradient descent; 2) three single learners with boosting as the meta-learning mechanism and classifiers include NB, SVM, and nearest neighbor; 3) similar to (2) but with bagging. The best result of the first study shows the NB single learner achieved F1 score of 90.05% (Haidar, Chamoun, and Serhrouchni, 2017), while the best results of the ensemble meta-learner shows 92.6% of F1 score (Haidar, Chamoun, and Serhrouchni, 2019). Thus, it is worth to try applying an enhancement to machine learning classifiers with ensemble meta-learning methods for this domain of problems.

In this study, our focus is on Natural Language Processing (NLP) techniques using machine learning approach and ensemble machine learning approach to analyze offensive language and hate speech in Arabic content of Twitter. Unlike previous Arabic offensive language detection studies, we do not incorporate Twitter user accounts into the classification model (Abozinadah, Mbaziira, and Jones, 2015; Abozinadah and ones, 2017; Abozinadah, 2017) and we do not implement deep learning models as earlier studies have done (Mohauouchane, Mourhir, and Nikolov, 2019). The data used in this study contains various offensive contents rather than limiting the content to specific source as Alakrot, Murray, and Nikolov (2018a, 2018b) which could narrow the types of offensive in samples into the context of the channel. For example, if the YouTube channel is a sport channel, then, the types of offensive language in the dataset reflect the nature of sport related offensive language. We train our models using linguistic features only. Moreover, the preprocessing steps we follow in this study are not identical to any of the preprocessing steps of the previous studies.

3. Data and Methodology

3.1 Data Description

We use the dataset provided by the shared task of the fourth workshop on Open-Source Arabic Corpora and Corpora Processing Tools (OSACT) in Language Resources and Evaluation Conference (LREC) 2020. The main goal of this shared task is to identify and categorize Arabic offensive language in Twitter. The organizers collect tweets through Twitter API and annotated them hierarchically regarding offensive language and offense type. The task is divided into two sub-tasks: a) detecting if a post is offensive or not offensive; b) identifying the offense type of an offensive post as hate speech or not hate speech. In addition, provider of the dataset performs some preprocessing to ensure the privacy of users. Twitter user mentions were substituted by
The dimensionality of the data by normalizing the variation of dialects on a set of nouns to be converted from dialectal Arabic to Modern Standard Arabic (MSA). For example, the variations of the word boy, ‘زول’، ‘رجل’، and ‘رجلة’ are converted to ‘رجل’.

3.2.3 Letters Normalization

Arabic letters can be written in various formats depending on the location of the letter within the word. We normalize Alif (א,א), Alif Maqṣūra (א,א), and Ta Marbūta († to ‡). Letters that were repeated more than two times within a word were reduced to two times only.

3.2.4 Hashtag Segmentation

Hashtags are commonly used in Twitter to highlight important phrases within the tweet. Thus, it is very important to consider hashtags during the preprocessing phase to convert hashtags into a meaningful format. For example, the hashtag ‘الله’ is converted to ‘الله’ which is easier for the system to understand and process.

3.2.5 Miscellaneous

Tweets were filtered to remove numbers, HTML tags, more than one space, and some symbols (e.g., "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "", "”,...
Thus, we chose to examine the effect of this slight difference behind the algorithms of the SVM and the logistic regression by training a logistic regression classifier. We chose the decision tree to examine the classification task using a non-linear model, as the decision tree classifier uses a set of conditions to classify new instances (Eisenstein, 2018). We experimented with different parameter settings, but we only report the best performing settings. The Logistic regression classifier was trained using word and character n-gram features (n = 1-4) with L2 regularization. The SVM classifier was also trained using word and character n-gram features (n = 1-4) with linear kernel and L2 regularization. The decision tree classifier was trained using the same features of the previous classifiers with gini criterion and best splitter. We used Python scikit-learn library to implement all models.

### 3.4.2 Ensemble Machine Learning Models

We trained three ensemble machine learning classification models, namely bagging, random forest, and AdaBoost. We select three different models each use different ensemble machine learning method. The bagging model runs a learning algorithm multiple times, in which randomly selected samples from the dataset are given to the learning algorithm in each run (Nadali et al., 2013). The random forest uses a final decision of the average prediction that is given by a single decision tree within a combination of multiple decision trees (Haidar, Chamoun, and Serhrouchni, 2019). The AdaBoost is a boosting ensemble machine learning model that depends on a sequential learning of classifiers; the single classifiers are tweaked based on the misclassified samples from the previous classifiers (Kaati et al., 2015). The final decision of AdaBoost is the weighted sum of outputs from a combination of the final classifications (Kaati et al., 2015). The bagging classifier was trained with learning rate of 1 and 50 maximum number of estimators. The random forest was trained using 100 maximum number of trees and Gini criterion. The AdaBoost was trained using a learning rate of 1 and 50 maximum number of estimators. All classifiers were trained using word and character n-gram features. We used Python scikit-learn library to implement all models.

### 4. Experiment Results

Figure 2 and Figure 3 shows the results for performance evaluation using precision, recall, accuracy, and F1 metrics. One observation from the figures shows the problem of imbalanced data, so that higher accuracy does not guarantee higher F1 score. Thus, F1 score is more informative for evaluating the classifiers. Among the machine learning models, the SVM based classifier performs the best with F1 score of 82% followed by the logistic regression based classifier with F1 score of 81%, and lastly the decision tree classifier with F1 score of 69%. Among the ensemble machine learning models, the bagging based classifier performs the best with F1 score of 88% followed by the random forest based classifier with F1 score of 87%, and at the end comes the Adaboost based classifier with F1 score of 86%.

These results demonstrate the effectiveness of using ensemble machine learning methods; F1 score increases from 82% using the best machine learning model to 88% using the best ensemble machine learning model.

### 5. Conclusion

Ensemble machine learning is a meta-learning machine learning method that aims to improve single learner classifier’s performance by combining predictions from multiple single learner classifiers. In this study, we investigate the effect of applying single learner machine learning approach (SVM, logistic regression, and decision tree) and ensemble machine learning approach (bagging, Adaboost, and random forest) on offensive language detection for Arabic language. Online offensive language classification task is very challenging due to the ambiguity...
and informality of the social media language, which increases the difficulties to achieve high performance, particularly for Arabic text that has multiple dialects. Results show promising impact for the ensemble machine learning approach over the single learner machine learning approach. Among the trained ensemble machine learning classifiers, bagging performs the best in offensive language detection with F1 score of 88%, which exceeds the score obtained by the best single learner classifier by 6%.

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