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Original Article

Predicting content-based political inclinations of Iranian Twitter users using BERT and deep learning

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ABSTRACT: Along with the advent of social networks such as Twitter; Politicians, social media, and ordinary citizens regularly turn to them to share their thoughts and feelings, such as political views. This article analyzes the political ideology of Iranian Twitter users using deep learning and combining the deep layers of LSTM and CNN with BERT, enabling us to target groups of sympathizers and opponents of the Islamic Republic of Iran that is of particular interest to political scientists. We trained a model for predicting whether a tweet is a sympathizer or opponent, using a novel dataset from Twitter, including tweets from sympathizers and opponent people. Then, using the trained model, the people's ideology can be identified. The results show that using the proposed model, tweets can be categorized with a 75.68% F1-Score, and the classification of individuals based on political orientation to a 93.18% F1-Score can be done correctly.

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1. Introduction

Along with the advent of social networks such as Twitter; Politicians, social media, and ordinary citizens regularly turn to them to share their thoughts and feelings, such as political views. This article analyzes the political ideology of Iranian Twitter users using deep learning and combining the deep layers of LSTM and CNN with BERT [8], enabling us to target groups of sympathizers and opponents of the Islamic Republic of Iran that are also of particular interest to political scientists. We trained a model for predicting whether a tweet is a sympathizer or opponent, using a novel dataset from Twitter, including tweets from sympathizers and opponent people. Then, using the trained model, the people's ideology can be identified. The results show that using the proposed model, tweets can be categorized with a 75.68% F1-Score, and the classification of individuals based on political orientation to a 93.18% F1-Score can be done correctly. Today, a lot of information can be extracted from social networks due to their increasing popularity among people in the community, from permanent information (friend and follow relationships) to temporary interactions (like, comment, repost) to general information (geographical location, profession) and the

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submitted content (texts, images, links) [9]. Also, according to studies, it can be shown that this information can be used to predict user information such as personality traits and ethnicity [2] [23]. Another user information that can be predicted from social networks is predicting the political inclination of individuals. For this purpose, the study of the political inclination of individuals in social networks as well as the analysis of behaviors and political views of individuals and groups have become one of the fields of interest for researchers in recent years. Millions of opinions, including political opinions, are being presented on social networks every day, and the constant political debates and propaganda on these social networks are visible.

Therefore, being able to identify the political orientation of individuals in these networks based on what they share can be a useful tool for analyzing individuals. In this paper, because our goal is to analyze people's shared posts, as well as to categorize people based on their similarities and to categorize political inclinations, we have used the textual information shared by these people on Twitter. We also assume that tweets contain enough information to understand people's political inclinations. Twitter, with millions of monthly active users, has now become a very good source of information for organizations and individuals who have a strong political interest in maintaining and strengthening their power and reputation. Millions of political opinions and debates are recorded on this social network daily, and many people in the society, as well as political celebrities, use this social network in Iran to share their political ideas and activities. One of the advantages of using Twitter is that it simplifies the process of extracting information about public accounts through existing APIs. This makes the data collection process much faster, more legitimate, and more accessible than other social networks. The most important reason is that Twitter has become highly politicized and its users express their political views more than any other platform [6].

In this paper, we have examined the recognition of the political inclination of those who is sympathizer and opponent of the Islamic Republic of Iran. For this reason, to evaluate different methods, we have gone to the collection of shared posts of politicians and celebrities, as well as people whose political orientation is evident from their tweets. At first, politicians were collected in two groups, for and against, and then, according to the relationship and activities of other people with these people, the required accounts for the two groups were collected. Based on this collected dataset, we have implemented a set of models based on deep neural networks and language models to predict the political sympathizer or opponent groups of the Islamic Republic of Iran. Using the implemented models and the obtained results, it is possible to identify the political opinion of the people active in the Twitter social network according to the background of the shared tweets. It can also be shown which category each person agrees or disagrees with and which category they are inclined to according to their opinions.

According to the above discussion, the work we have done in this article is as follows:

- We have collected a novel dataset including 123,591 samples of tweets of people with political tendencies in sympathizers and opponents of the Islamic Republic of Iran to design a model for classifying political people. This dataset is a good and rare resource for working in this field.
- We used a semi-automated method to annotate the collected tweets.
- We have used models based on deep learning and language models and fine-tuned them to categorize tweets.
- Using this dataset, we first tried to present a model that categorizes the tweets related to the sympathizers and opponents. Then we show that using the proposed model, people can be categorized according to the background of their tweets.

The organization of the rest of our paper is as follows: In section II, the previous and related works in this field are described. In section III, we introduce the used dataset and analysis it. section IV will include the presentation of implemented models and their details. In section V, we will evaluate the results obtained in this work, and finally, we will have conclusions and suggestions.

2. Related Works

There is a lot of related work on Twitter analysis in recent years. Many of these studies have been concerned with analyzing the political sentiments of individuals in different countries or categorizing their political inclination. In related work, the use of machine learning models for deep learning techniques as well as the use of language models can be seen. This section is intended to provide an overview of the main previous work related to this field. In [10] they have shown a systematic connection between the real world and social network data. They have shown that there is a connection between political tweets and election results, according to the two congressional congresses. In [16] with the help of the machine learning model and the analysis performed, it has been shown that Twitter political analytics can be a better alternative or a good complement to online or telephone polls. To identify the political orientation of individuals in [7], a good analysis has been done and it has been shown that using the semantic analysis embedded in the content of users' tweets, the hidden structure of the data is strongly dependent on the political orientation. To categorize the political orientation of people in Italy into different political groups, by using the tweets they shared on Twitter in [9], many machine learning classifiers with different types of vectorized features have been used and examined. [19] also explores methods for classifying people into Republicans and Democrats on Twitter. In this study, textual and non-textual features of Twitter users were used for analysis. As a result, they have been able to achieve good classification accuracy by using different features. Much of Twitter's political analysis research has also focused on election predictions using different features and datasets collected [3] [18]. Another related work in the political classification of individuals in Italy is [6]. In this study, machine learning classifiers such as SVM and Random Forest have been investigated to predict two political groups. Then, the presented models are used to deduce the political orientation of people and it has been able to categorize users into two different categories with high accuracy. In [29], supervised machine learning methods, including a combination of language features such as TF-IDF, Bi-grams, Tri-grams, and other metadata features are used to classify and predict the political polarity of a tweet. The political orientation of users based on tweets related to the constitutional referendum in Italy is also examined in [5]. [22] presents a dataset to identify the political orientation of individuals in different categories in the United States. Using this dataset, which is collected as a self-report of people of their political affiliation in seven different political categories, they provided a model to determine the political affiliation of individuals on Twitter. Also, a lot of related works in the United States to determine the tendency of people in conservative and liberal categories with different approaches and good accuracy has been reported [1] [28] [25]. In this study, as mentioned, our goal is to categorize the political Inclinations of tweets, followed by the categorization of people's political Inclinations using deep learning techniques and language models. In the use of deep learning models and language models in the classification of political tweets, we can mention [9]. They were able to provide a classifier for stance tweet prediction using fine-tune BERT [8] based on the collected dataset, which was semi-automatically annotated. Another related work that uses BERT for political analysis is [13], which according to BERT, provides an analysis of political Inclinations on social network data. Other language models such as XLNet [30], RoBERTa [15], and DistilBERT [24] have also been used to analyze and classify political texts in [27] [4].

3. Data Collection, Description and Labeling

To prepare the required dataset to classify the political Inclinations of people into two groups of sympathizers and opponents of the Islamic Republic of Iran, Twitter data is crawled using the Twint [1] scraping tool. This process has been done in two steps: 1- Manually searching users, checking their tweets, and selecting the appropriate accounts in two categories of sympathizers and opponents. 2- Crawling all the tweets of these people. This dataset contains more than 123K tweets belonging to 106 unique Iranian users, which are annotated according to their political orientation. After collecting the accounts and tweets of these people, we have split them into train, test, and validation sets, which the details of this split are shown in Table 1. This slit is random and based on the number of users.

	Total	**Train**	**Test**	**Validation**
# of accounts	106	62	22	22
# of tweets	123,591	71,142	37,314	15,135

Table 1: Statistical information of dataset

In natural language processing, normalizations are usually done on the datasets to clean up existing texts. After collecting the dataset, we have also done some pre-processing on the tweets because the tweets on Twitter contain a lot of noise and cannot be used directly. These normalizations include:

- Deleting extra space and blank lines
- Deleting punctuations
- Deleting links from all tweets
- Deleting non-Persian characters
- Changing Arabic characters to Persian

[1] https://github.com/twintproject/twint

- Normalization by HAZM [2]

The details of dividing the number of tweets of each category in each collection are shown in Figure 1.

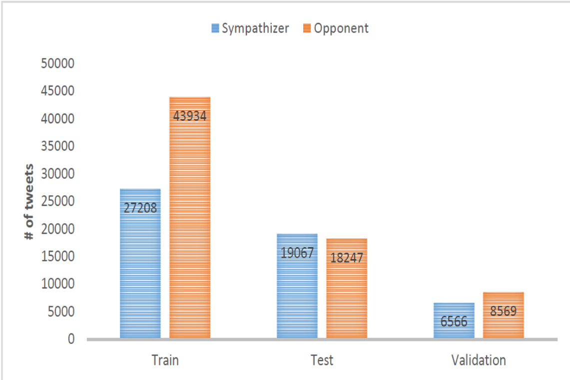

Figure 1: Distribution of the tweets in the dataset

As it is obvious, in the dataset of this study, as in all real-world problems, there is the problem of data imbalance. One of the reasons for the imbalance of the dataset, which is evident in train data, is that the dataset is split based on user accounts, that is, first the user accounts are split into sympathizers and opponents and then the tweets of these users' accounts are collected. This has caused the number of tweets to be unbalanced in the two categories. The histogram of the length of the tweets is shown in Figure 2.

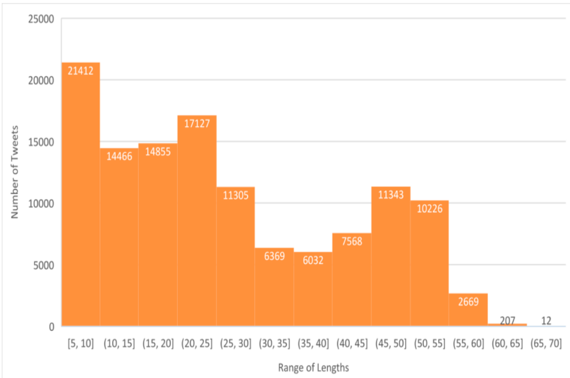

Figure 2: Histogram of lengths of samples (tweets)

4. Methods

Different methods of supervised learning have been used to categorize people based on their political orientation. As described in the previous sections, these methods include the use of deep learning methods and the BERT. In the beginning, we tried to have a classifier to categorize tweets. Then, using this classifier, we can classify people into two categories, sympathizers and opponents of the Islamic Republic of Iran, according to their political orientations. Due to the specificity and novelty of the dataset and its collection for this specific task, there was no basic model for assessing the accuracy of the base. Therefore, to evaluate the base model, two models, LSTM-Att and Convolutional Neural Network (CNN), have been used to have an initial evaluation of the dataset.

4.1. LSTM-Att and CNN

In the LSTM-Att structure, due to the proper performance of the recurrent layers in the text data, several layers of the series LSTM with fully-connected layers attached at the end have been used. It is important to note that this basic structure of LSTM has been used with the concatenation of the attention mechanism to determine the significance of each word.

[2] `https://github.com/sobhe/hazm`

In the implemented CNN structure, three parallel convolution layers are used to extract local features with different filter sizes along with the max-pooling layer to reduce the dimensions and at the end and the fully connected layers.

4.2. APCNN_LSTM

One of the proposed models in this paper includes the combination of CNN neural networks, LSTM layers, Attention mechanism, and max-pooling. In this study, to investigate the functionality of parallelism and to extract the relevant features of each layer, the parallel connection of these layers has been used. In this way, the output of the word embedding layer enters the LSTM and CNN layers in parallel. So that on one side of the model, two layers of LSTM series are used to extract the feature, the output of the first layer is given along with the output of the embedding layer or the features of the words level as input to the second layer. In this part of the model, due to the proper performance of bidirectional recurrent layers in learning the dependence between input tokens, BiLSTM layers are used, and to preserve the word level feature, the residual connection layer is given to the second layer. In the other part of the model, three CNN layers with different filter sizes are used to extract higher-level features than word features. Using CNN layers helps to extract local features. The output of these convolution layers is given to a BiLSTM layer to extract better features. Finally, the output of the parallel channels is concatenated and the attention mechanism is considered to understand the importance of each word or to focus on the difference in the output of the layers. This study also uses this proposed model called APCNN_LSTM.

4.3. BERT and ParsBERT

One of the language models that has been well received in the last few years and has been able to make good improvements in many downstream tasks is the BERT language model developed by Google. This language model has been trained in two architectures, 8 and 12 layers of encoder-decoder, and on a huge dataset of books and Wikipedia[3]. BERT is trained based on the two tasks of the next sentence prediction and Masked Language Modeling(MLM). Also in 2020, the ParsBERT [12] language model was presented on a huge Persian dataset. These language models can be used in the task of classifying texts in two ways: feature extraction and fine-tuning. In this study, both BERT and ParsBERT models are fine-tuned on the dataset. These pre-trained language models can help to extract features and better classify tweets due to the strong structure of the model and training on large text files. In fine-tuning, the input sequence is tokenized by the BERT tokenizer, and the last hidden state and a softmax layer are used to identify the tweet label.

4.4. BERT with Deep Neural Networks

Word2Vec [17] and GloVe [20] methods are pre-trained word embedding methods that are trained based on neural networks and follow semantic and syntactic relationships between words to provide word representation vectors. In this paper, we have used the pre-trained words embedding in [26] to train the basic deep learning models of LSTM-Att, CNN, as well as the proposed APCNN_LSTM model. This word embedding (skip-gram) has been trained on 8 million tweets and has 300-dimensional vectors for each word. But unlike these methods, contextual word embedding methods such as BERT and ELMO [21] provide dynamic word embedding by considering the context. Another model in this study involves the use of BERT embedding in the APCNN_LSTM model as word embedding. As explained in the previous sub-section, one of the uses of language models is to extract features or their word embedding. In this research, we use both BERT and ParsBERT, along with a combination of the proposed model called ParsBERT_APCNN_LSTM and BERT_APCNN_LSTM.

5. Evaluation and Results

In this section, we will first discuss the details of the implementation of the models, and after introducing the metrics and evaluation methods, we will analyze the results obtained in this study on two levels: the results of tweet classification and user classification based on political inclination.

5.1. Implementation Details

To implement the models in this study, we used the PyTorch-Lightning framework [11] and the models were trained using a GeForce GTX 1080 Ti GPU. In training the models, we have used dropout to reduce the over-fitting after the words embedding layers and the recurrent layers at the rate of 0.2. The batch size is tuned among [32,64]. The LSTM-Att model consists of two bidirectional layers with the hidden size of 256. Also, in CNN model, three parallel

[3] https://en.wikipedia.org/wiki/Main_Page

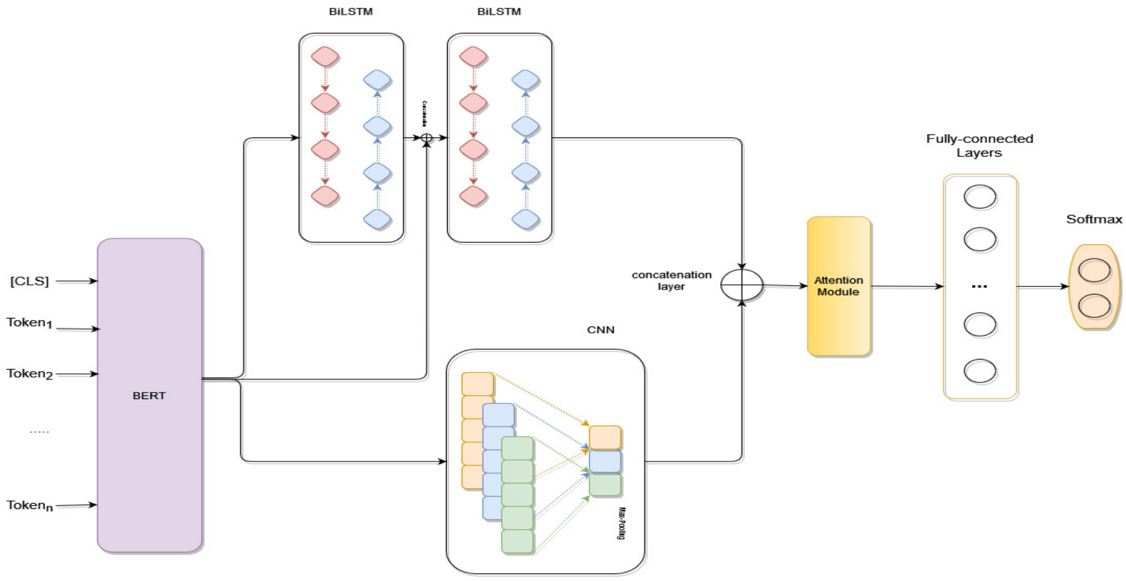

Figure 3: Architecture of proposed model (ParsBERT_APCNN_LSTM)

layers with the number of filters 512 and the filter sizes of 3, 4, and 5 are used. The proposed APCNN_LSTM model also uses 128 hidden size for recurrent layers and 256 filters with sizes of 4, 3, and 5 for CNN. When using pre-trained word embedding, the maximum sample length is set to 70, and when using BERT, the maximum sentence length is set to 100. In these cases, a sample longer than these values is truncated and a sample shorter is padded to the maximum. We have used the Adam [14] optimizer function with 2e-5 learning range.

5.2. Performance Metrics

To evaluate different models, different metric scores have been selected to gain an accurate insight into the quality of the predictions. A true positive (TP) is a sympathizer tweet labeled as a sympathizer, a true negative (TN) tweet is an opponent tweet labeled as an opponent, a false positive (FP) is an opponent tweet labeled as a sympathizer, and a false negative (FN) is a sympathizer tweet labeled as an opponent.

- Accuracy is the percentage of tweets that are properly tagged and defined as follows:

$$\begin{aligned} Accuracy &= \frac{\text{Number of correct classifications}}{\text{Total number of test cases}} \\ &= \frac{TN + TP}{TN + TP + FN + FP} \end{aligned} \tag{1}$$

- Precision measures the percentage of tweets that are sympathizers out of all that is predicted as a sympathizer, and it is defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- Recall measures how many sympathizer tweets are labeled as a sympathizer and it is defined as follows:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

- The F1-score seeks a balance between precision and recall and is defined as follows:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

In this study, two different types of evaluations have been performed: 1) Evaluation of test and validation set in terms of category detection of each tweet. 2) Evaluation of identifying individuals in terms of political inclination.

After training the developed models, each model is evaluated using the evaluation metrics described in the previous section, to check their accuracy on the test and validation data and also to be able to have a comparison between them. After evaluating the models, the model that was able to obtain the best F1-score among the others in the test data was evaluated to identify individuals in terms of political inclination. To categorize people in terms of political orientation, a set of people whose tweets were in the test and validation set was used. In this way, all the tweets of these people have been given to the model and predicted a label of sympathizer or opponent for them. Then, if the number of labels identified as sympathizers was more than the number of labels identified as an opponent, the person was assigned as a sympathizer person and vice versa.

5.3. Results and Discussion

In this part, we will analyze the results obtained by the models and compare them according to different metrics. The results obtained by the models in the three train, test, and validation set based on F1-Score are shown in Table 2.

Model	Test	Validation	Train
LSTM_Att	73.55	70.58	84.40
CNN	73.83	70.80	88.94
APCNN_LSTM	75.08	73.51	88.67
mBERT	68.35	76.65	89.22
ParsBERT	72.15	76.58	90.05
mBERT_APCNN_LSTM	70.30	77.57	97.52
ParsBERT_APCNN_LSTM	**75.68**	77.91	89.90

Table 2: Performance comparison (F1-score %) of models

As shown in Table 2, ParsBERT_APCNN_LSTM has been able to achieve the best performance in the test set with an F1-Score of 75.68% compared to other models studied. The APCNN_LSTM model, due to the simultaneous extraction of temporal features by LSTM layers, as well as local features by CNN and the combination of these features, for use in tweet categorization, was able to improve by 1.25% and 1.53%, respectively in CNN and LSTM-Att models that use only one type of feature. Using fine-tune language models, as shown, can not in itself improve the performance of the classification on this task and this dataset, but by combining deep learning models with them, it has been able to have the best performance among the models. The mBERT_APCNN_LSTM model was able to improve by 1.95% compared to mBERT and also the ParsBERT_APCNN_LSTM model was able to improve by more than 3.5% compared to ParsBERT. According to these results, it can be said that using the word embedding of language models instead of pre-trained word embeddings as word-level features and using a hybrid model with LSTM and CNN layers on top of this word embedding can improve the tweets classification. The comparison of these models in different sets is shown in Figure 4.

The results of the F1-score metric for the two classes of sympathizer and opponent in the ParsBERT_CNN_LSTM model are shown in Table 3.

	F1-Score	Total Accuracy
Sympathizer	73.32	76.69
Opponent	75.75	

Table 3: Results of the proposed model for each category (%)

As mentioned, one of the other evaluations done in this study is the evaluation of the political category of individuals, being in the category of sympathizer or opponent. People whose tweets are in the validation and test set and include 44 people were used. First, all the tweets of these people are evaluated by the model, and then for each person, according to the majority of the predicted labels, a label for sympathizer or opponent is considered. According to this evaluation, the proposed model was able to achieve 93.18% accuracy in correctly predicting the category of political people. The details of this evaluation are shown in Table 4.

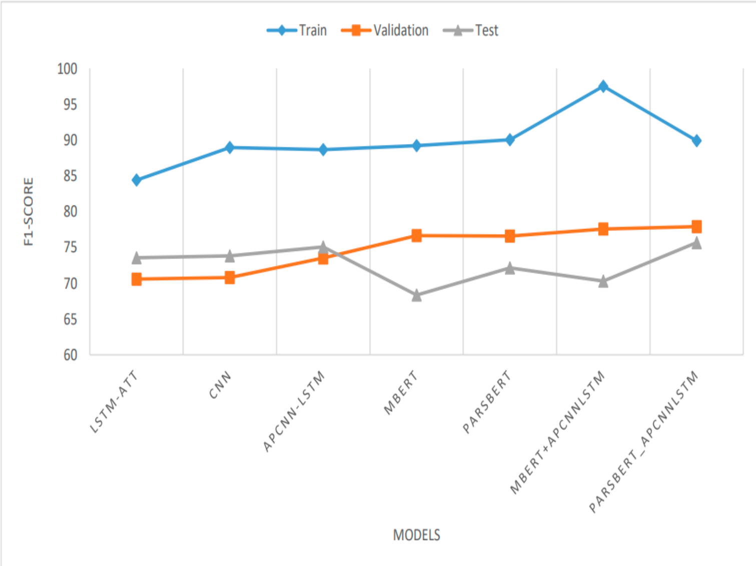

Figure 4: Comparison of models in different sets (%)

	F1-score	Recall	Precision
Sympathizer	93.33	95.45	91.30
Opponent	93.02	90.90	95.23
Total Accuracy		93.18	

Table 4: Results of classifying people based on political inclination (%)

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