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Aspect-Based Sentiment Analysis Based on Users' Comments in an Online Marketplace

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Abstract
In recent years, with the expansion of online shopping and the importance of user feedback in improving the quality of products and services, sentiment analysis of user reviews has become one of the most important tools and opportunities for online businesses and services. In this research, various approaches based on Convolutional Neural Networks (CNN), BERT language model, and FastText language model have been examined for sentiment analysis of user reviews about mobile phones in aspects such as camera, battery, and price in an online marketplace. In this regard, the data were labeled based on aspects and categorized into three sentiments: positive, negative, and neutral. Additionally, to improve the performance of the proposed approaches and address data imbalance, data augmentation methods were utilized and their impact was analyzed. Finally, using the proposed models, very high accuracy in detecting positive, negative, and neutral reviews in each aspect was achieved. According to the results, the proposed CNN-based approach performed better than the other two proposed methods on the given data.

Keywords:
Sentiment analysis, FastText; Different aspects of comments, Deep learning, Convolutional neural network, BERT.

1. Introduction

With the expansion of web usage, online shopping, and users' online interactions in recent years, user feedback and opinions have been introduced as a valuable resource in the web environment [1]. These factors enable organizations to improve their services and products by more accurately analyzing these inputs and user opinions. To achieve these objectives, organizations employ sentiment analysis, which involves the evaluation and analysis of user opinions in order to better identify and understand their emotions, concerns, and preferences [2-4]. With the help of these analytical tools, organizations gain deeper insight into customer reactions and needs and, as a result, make better decisions. The most important reasons for the significance of sentiment analysis in businesses include understanding customer needs, improving the quality of products and services, increasing customer satisfaction, attracting new customers, and predicting future problems [5,6].

Despite recent advances, some of the most important challenges of sentiment analysis in the Persian language include data scarcity, structural complexity, and lexical ambiguity. Many Persian words have different meanings depending on the context. Proper understanding of these words requires accurate text analysis and correct identification of their usage [7,8]. To improve the accuracy and efficiency of sentiment analysis in Persian, the development of advanced models and solutions to address these challenges is essential [9-12].

This research has been conducted with the aim of analyzing user sentiments toward various aspects of mobile phones in an online marketplace and examining the data preprocessing process in the Persian language. The proposed approaches include a Convolutional Neural Network, a BERT language model fine-tuned on the data, and a FastText language model, with the goal of improving the accuracy and efficiency of these models in Persian sentiment analysis. A dataset consisting of user reviews about mobile phones was created, labeled as positive, negative, and neutral based on different aspects. In addition, data augmentation and data balancing methods were used to improve model accuracy.

2. Methodology

The overall process of this research is shown in Figure 1.

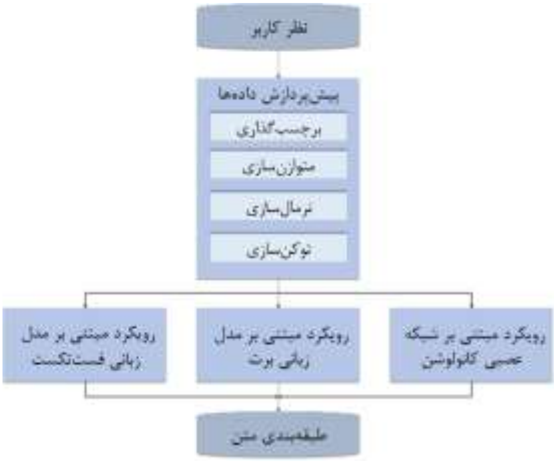

Figure 1. Proposed approach for aspect-based sentiment analysis

2.1. Data and Preprocessing

The data were collected from the Digikala website as an online marketplace. A total of 1,807 user reviews were manually labeled for the camera, battery, and price aspects in three classes: positive, negative, and neutral. Then, due to the time-consuming nature of manual labeling, an automatic labeling method was used to label 4,373 reviews. The final dataset consists of a total of 6,180 reviews.

One of the first steps in natural language processing tasks is data preprocessing. The Hazm library was used for data preprocessing, and to prevent overfitting, data balancing was applied to achieve better performance in less frequent classes and balance in evaluation. In the text normalization stage, correction of spacing in prefixes and suffixes, removal of diacritics, elimination of redundant repeated letters, replacement of some letters and symbols with Persian equivalents, and replacement of English numerals with Persian equivalents were performed. In the tokenization stage, considerations related to semantic preservation were addressed, including handling punctuation marks (preserving punctuation marks as separate tokens), preserving non-breakable prefixes (such as "می" in "می‌خواهم"), and controlling spacing. The Easy Data Augmentation method (using the nlpaug library) consists of four simple yet powerful operations: synonym replacement, random insertion, random swapping, and random deletion.

2.2. Applied Approaches

For sentiment analysis using the Convolutional Neural Network, after tokenizing the data and converting the text into numerical form, an embedding layer was used to transform these numbers into numerical vectors. The Conv1D layer has a filter size of 128 and uses the ReLU activation function. After each convolutional layer, a pooling operation is applied, and finally, fully connected layers are used to combine and transform the extracted features into the final output. In the final stage, a dense layer with the Softmax activation function is used to compute output probabilities for final classification. In addition, during model construction, after the feature extraction stage, a dropout layer is used to prevent overfitting and increase model generalization.

For sentiment analysis using the BERT model, after data preprocessing, tokenization was performed using the BERT tokenizer. Then, a pre-trained BERT model was used and fine-tuned on the data. The FastText model was also trained using the preprocessed data. Using the Word2Vec algorithm, word embeddings were created by exploiting shared word meanings, generating numerical vectors for each word, and the model was trained for text classification.

To implement the proposed approaches, in all experiments the Sparse Categorical Cross-Entropy loss function, suitable for multi-class problems, the Adam optimizer, and a learning rate of 0.00001 were used. The ratio of test data to validation data was set to 0.3, and the k-fold value was set to 5. The number of epochs was considered as 1, 5, and 10, and two evaluation metrics—accuracy and F1-score—were used. For implementing the Convolutional Neural Network for text classification, the Keras and TensorFlow libraries were used, and the model was trained and evaluated using the ReLU and Softmax activation functions and appropriate hyperparameter tuning.

3. Discussion and Results

Table 1 reports the results of the Convolutional Neural Network approach on the final dataset. The "Balanced" column refers to data augmentation.

Table 1. Results of the Convolutional Neural Network on the final dataset

Epochs		5		10	
Aspect	**Balanced**	**Accuracy**	**F1-score**	**Accuracy**	**F1-score**
Camera	**No**	78/58	69/92	95/90	75/42
	Yes	92/82	77/41	97/92	77/45
Battery	**No**	81/45	61/45	87/09	71/31
	Yes	93/85	79/99	97/43	80/17
Price	**No**	80/48	84/74	95/51	80/89
	Yes	91/25	78/48	**98/66**	**88/94**

In the BERT approach, a model pre-trained on Digikala user reviews was used via the Hugging Face platform. Table 2 reports the results of the BERT approach on the final dataset with 1 and 5 epochs.

Table 2. Results of the BERT language model on the final dataset

Epochs		1		5	
Aspect	**Balanced**	**Accuracy**	**F1-score**	**Accuracy**	**F1-score**
Camera	**No**	88/29	88/88	88/76	89/68
	Yes	90/34	90/37	91/86	93/04
Battery	**No**	91/93	91/71	92/43	92/14
	Yes	93/52	93/71	**95/11**	**96/36**
Price	**No**	89/85	89/18	90/13	89/20
	Yes	90/55	90/86	92/77	93/46

For implementing the FastText model, the FastText library was used. For this purpose, n-gram values of 2 and 3 were considered, with the value of 3 yielding better results. Table 3 reports the results of the FastText approach on the final dataset.

Table 3. Results of the FastText language model on the final dataset

Epochs		1		5	
Aspect	**Balanced**	**Accuracy**	**F1-score**	**Accuracy**	**F1-score**
Camera	No	69/34	60/73	72/78	67/70
	Yes	78/61	72/17	82/67	80/42
Battery	No	70/23	69/50	75/63	70/77
	Yes	82/63	77/97	85/79	84/30
Price	No	74/27	72/52	75/54	73/08
	Yes	83/83	76/15	**90/13**	**89/30**

4. Conclusions

In this research, three different approaches were used for sentiment analysis and text classification into positive, negative, and neutral sentiments across three aspects: camera, battery, and price. In addition, by examining data balancing methods, their impact on the results of each approach was evaluated. Based on the results, the Easy Data Augmentation method with random swapping operations for data balancing had a positive impact on model performance and led to improved results. In this study, the BERT approach achieved the best results in terms of F1-score across all three aspects; however, the execution time for training and evaluation for each aspect exceeded 160 minutes. Using the Convolutional Neural Network, the best results in terms of accuracy were achieved across all three aspects. The execution time for training and evaluation for each aspect ranged between 100 and 120 minutes, which is more favorable than the BERT model in terms of time to obtain results. The FastText language model also yielded good results across all three aspects. The advantage of this method is its very short execution time, with training and evaluation for each aspect taking less than 10 seconds, which is significantly faster than the other two approaches. In their best performance, the Convolutional Neural Network, BERT, and FastText models achieved F1-scores of 94/98, 36/96, and 30/89 percent, respectively.

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