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Research paper

Automatic Persian Text Emotion Detection using Cognitive Linguistic and Deep Learning

Seyedeh Sareh Sadeghi[1], Hasan Khotanlou[2*] and Mohammad Rasekh Mahand[3]

1. Faculty of language and humanities, Bu Ali Sina University, Hamedan, Iran.

2. Department of Computer Engineering, Bu Ali Sina University, Hamedan, Iran.

3. Faculty of language and humanities, Bu Ali Sina University, Hamedan, Iran.

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**Corresponding author: khotanlou@basu.ac.ir (H. Khotanlou).*

Abstract

In the modern age, the written sources are rapidly increasing. A growing number of this data is related to the texts containing the feelings and opinions of the users. Thus reviewing and analyzing the emotional texts have received a particular attention in the recent years. In this paper, a system that is based on a combination of the cognitive features and the deep neural network, gated recurrent unit, is proposed. Five basic emotions used in this approach are anger, happiness, sadness, surprise, and fear. A total of 23,000 Persian documents by an average length of 24 are labeled for this research work. The emotional constructions, emotional keywords, and emotional POS are the basic cognitive features used in this approach. On the other hand, after pre-processing the texts, the words of the normalized text are embedded by the Word2Vec technique. Then a deep learning approach is followed based on this embedded data. Finally, the classification algorithms such as Naïve Bayes, decision tree, and support vector machines are used in order to classify the emotions based on the concatenation of the defined cognitive features and the deep learning features. 10-fold cross-validation is used in order to evaluate the performance of the proposed system. The experimental results show that the proposed system has achieved an accuracy of 97%. The result of the proposed system shows the improvement of several percent in comparison with the other results achieved by GRU and cognitive features in isolation. At the end, studying other statistical features and improving these cognitive features in more details can affect the results.

1. Introduction

Emotions have been studied in a verity of sciences such as anthropology [1], psychology [2], and linguistics [3] in order to recognize the unknown aspects of the humans. As the automatic detection of humans plays an important role in many domains, it has attracted the attention of the researches. For example, recognizing the real emotions or the latent emotions of sick persons can help the psychologists to treat their patients. The more interaction of computers and humans can also help the engineers to improve their systems. Studying the users' comments about a special product can help others to know about the advantages and disadvantages of the products.

Recognizing the emotions of the humans by computers has been called automatic emotion detection, which can be done based on the sounds [4], images [5], and texts [6]. The text detecting emotion has been studied less than the other two domains. Today, the huge amount of information that exists on the networks makes the text emotion detection an important domain to study. Due to the existing difficulties, this task seems so challenging. For example, detecting the real emotions of the humans is sometimes difficult. Sometimes people use the words that do not show their real emotions directly. Another point is that the style of writing for each person is not the same. The formal and informal styles are difficult to be recognized. These cases are examples that make detecting the emotions not as easy as it seems at the first look.

In this research work, we try to use the cognitive and neural features in order to attain a high precision and recall. Regarding the emotional constructions and keywords besides neural networks for Persian texts is the novel aspect of this project. As recognizing the emotional keywords dos not seem to acquire the suitable performance, this research work pays attention to studying the syntactic, semantic, and pragmatic contexts of the documents. The Word2vec algorithm was used in order to reconstruct the semantic relation of the words. Furthermore, the deep learning algorithms were used to extract the features from the embedding words. At the end, the dense layer and cognitive linguistic features obtained were the features proposed for the classification of emotions. These features were used in the classification algorithms such as naïve Bayes, decision tree, and support vector machines. The experimental results were validated by a 10-fold cross-validation.

In view of the above, the purpose of this work was to provide a system for recognizing emotion based on the characteristics of cognitive linguistics so that it could have the function of a system similar to the function of the human mind. It also shows that in the modern age, the use of statistical science is very helpful in studying the underlying parts of the language.

The rest of the paper is structured as what follows. In the second section, we look at the related works done in this domain. In the third section, the proposed system is described regarding its features. This section discusses what the defined features are, how they are prepared, and how they are used. At the end, in the fourth section, the experimental results show the performance of the proposed system. It deals with the extent to which the defined characteristics influence the identification of various emotions

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2. Related Works

An overview of most of the past works shows that the methods used for the sentiment analysis systems can be divided into the following groups:

- Keyword approaches
- Machine learning approaches
- Combinative approaches

The earliest researchers have worked on identifying and using the keywords that directly reflect the sentiment expressed in the text [7]. Several methods have been used in order to identify these keywords. The accuracy of these methods depends on the presence of the keywords. One of the disadvantages of this method is its dependence on the specific areas [8]. Generally, in this approach, a list of words is prepared with the semantic labels of positive and negative emotions or feelings of sadness, happiness, etc. [9]. Sometimes the list is provided by giving points that indicate the intensity of an emotion. Then the text is fragmented into separate words. Next, the words that cover the emotion are determined. The intensity of the emotion is then measured. In the next step, it is discussed whether the verb is a negative one or not. Being a negative verb will change the determined emotion.

Unlike the keyword-based approaches, the machine-learning based approaches, by using pre-trained classifier systems, try to identify the sentiment expressed in the text. The lack of dependence on the specific domains has led to the rapid progress of the supervised and unsupervised machine learning methods.

Due to the lack of tagged emotional resources available, Twitter pages and hash tags used by the users have been used as the available processing resources in many studies [10]. Using these datasets and the categorization method of support vectors, the accuracy has been obtained to be close to 80%. These results indicate that these datasets can be used as the active datasets for processing. What is common in most research works is the use of different datasets, features, and classification methods in order to achieve a better accuracy. For example, in a similar work, the accuracy of 73% has been achieved using the support vector machine algorithm [11]. The features such as monogram, bigram, keywords, using semantic ontologies for semantic relationships of keywords and syntactic categories, and syntactic roles of bigrams have been used for the above-mentioned research works.

One of the problems that arise is the sentiment analysis of texts produced by users in outlets such as Twitter. One of main the tasks of sentiment analysis is subjectivity classification [12]. To this end, a subjectivity lexicons in which the words into objective and subjective words has been provided. Three metaheuristic methods have been used for this aim. It is observed that genetic algorithm performs better than simulated annealing and asexual reproduction optimization, and it also outperforms all the baselines in terms of accuracy in two of the three assessed datasets.

In addition to using the data and machine learning algorithms, sometimes the use of different psychological theories has made the same effect on the results obtained. Using the same data and features besides other categorization techniques such as Naive Bayes, Decision Tree, KNN, and support vectors has resulted in the accuracy close to 90% [13].

Other research works in this field include the neural network-based methods [14, 15]. Some of the common neural networks used in this section include the CNN, bi-LSTM, and GRU networks. The transfer learning, word embedding, and self-attention mechanisms are the techniques that can be used in this method in order to improve the experimental results. Evaluating sentences in different perspectives to capture the multiple emotions that exit in a single text is the novelty of these works [16]. Some of the common neural networks used in this section include the CNN, bi-LSTM, and GRU networks

The research works in the area of latent semantic analysis are the cases of unsupervised methods done in this domain [17]. Emotional corpora, designed over time, such as SemEval, ISEAR, were used as datasets. Then the dimensions of the key vectors were reduced by the use of LSA, PLSA, and NMF. At the end, classification was done by the use of similarity casinos. The results obtained showed that the NMF method performed better than the other two and achieved an accuracy of 73%. The use of PMI has been another method used in this field [18]. Providing a list of words related to a specific domain in order to extract the features is another method that can be used with the PMI and LDA algorithms.

The role of aspects in sentiment polarity classification and developed various techniques to assess the sentiment polarity of each aspect has been also studied. In this study, a Hierarchical Attention-based Method for aspect-based polarity classification of the text has been used [19]. The experimental findings on the SemEval2014 data set show that HAM can improve accuracy by up to 6.74% compared to the state-of-the-art methods in aspect-based sentiment classification task.

An example of the Persian studies done include an unsupervised case that has been attempted to be independent from a particular domain [20]. Attention to the keywords, intensifiers, and negative words was among the issues investigated in this work. The results obtained showed an average accuracy of 82%. Another study used news sites as the training data [21]. It paid attention to the cases like the grammatical features of words and analysis of emotional semantics. It achieved an accuracy of 42%. Another proposed model considers the features extracted from the text in two formats: 1-gram and 2-gram [22]. The emotional texts are classified into different emotional categories using the Bayesian method. Also by filtering the features and thus reducing their dispersion, 91.6% and 43% precisions are obtained for the 1-gram and 2-gram features, respectively. Another case of study is the method that has been followed according to the dictionary and support vector machines [23]. It has determined the positive and negative aspects of the dataset of the users' opinions about the Kish hotels. Multiplying the presence or absence of each word in its polarity value has gained an accuracy of 83%.

One of the problems in recognizing emotion is the lack of Persian emotional corpus that makes it possible to compare the results obtained from the studies. Thus, this research work, by spending a long time, has managed to provide emotional corpus with a volume of 23,000 documents so that from now on it can be used for the people who wish to study in this field. Another advantage of this method is that in addition to paying attention to the keywords and grammatical structures, the metaphorical and metonymic emotional structures have also been considered. Finally, in order to show the semantic relationships between the words, we have tried to use the deep learning method, which is an important method in machine learning.

3. Methodology

Determining the type of feeling expressed in a text and evaluating the effectiveness of the proposed features are the purpose of the proposed method.
Using the Bijan Khan corpus [23], emotional corpus of fear, sadness, happiness, anger, and astonishment was prepared. At first, the

documents were pre-processed in order to improve the system performance. Then the data was examined on the basis of the cognitive feature in order to see if these features were present in the texts. On the other hand, the data was embedded in Word2Vec vectors. In the following, embedding vectors are given to deep learning algorithms to produce dense layers. The deep learning classification approach used in this work is Gated Recurrent neural network approach. Then dense layers with vectors of cognitive features are concatenated. The resulting vectors are given to the classification algorithms in order to determine the emotion of each document. At the end, the final results are evaluated by a 10-fold cross-validation. Figure 1 presents an overview of the proposed method.

3.1. Emotional Corpus

The use of appropriate datasets is one of the factors that greatly influence the accuracy and measurement of the natural language processing systems. For this purpose, one of the first steps taken is to provide an appropriate corpus of data relevant to the selected purpose. For example, in scientific texts, as it is evident from their names, the use of sentences with emotional structures seems odd. Also it seems quite natural to use emotional sentences in narrative texts. On the other hand, although there are many written sources, there are very little emotional sources for NLP, especially for the Persian language. This led to prepare an emotional corpus in the first step. The previous research works done on the Persian language have usually been done by the users' comments about a particular product or daily news. In fact, there is no adequate and comprehensive dataset to evaluate the results of the proposed systems. This led to the first step in providing the emotional data from Bijan Khan's corpus that is one of the most popular corpora in the Persian language.

Among the Persian sources that exist, Bijan Khan's corpus was selected for being labeled emotionally due to its diversity in the contents of its documents. Bijan Khan's corpus is a collection of Persian texts containing more than 6 million words that have been professionally labeled with syntactic category tags. This collection contains more than 4,300 subject tags such as political, historical, scary, and fictions for the texts. After studying the documents in the body for each one of the five basic emotions (fear, happiness, sadness, anger, and surprise), a corpus was selected. This corpus was made manually by linguists, and it took a very long time to prepare it. Attempts were made to select the texts that contained only one emotion and selected texts to be prototype for the defined emotion. The prepared emotional corpus consisted of 23,000 emotional documents. The average length of documents was 24 words. In Table 1, the frequency of emotional documents is presented.

Table 1. Frequency of emotional document

Emotional text	**Text frequency**
Happiness	**6.144**
Sadness	**5.366**
Anger	**4.045**
Fear	**4.536**
Surprise	**3.443**

3.2. Text Pre-processing

There exist several challenges for the Persian language for being processed. One of the challenges for the Persian language processing systems is the complexity of its writing system. For example, an inappropriate use of distance rather than half-distance can be noted. Paying attention to the use of Persian punctuation and the use of non-Arabic letters can reduce the complexity of the writing system. Other challenges include the words that can be written in several ways. Identifying compound words and considering them as a single word are cases of other challenges that exist for the Persian language writing.

The pre-processing stage deals with normalization, stemming, part of speech tagging, and deletion of stop words in order to prepare the text for main processing. The pre-processing sections will increase the accuracy and performance of the system. For example, stemming of words is for considering a unit for the words related to the single root. Thus it easily affects the performance of the system. Stop words include the grammatical words such as conjunctions, and prepositions. These words lack semantic and contextual information. In the case of studies that focus on word frequency, the high frequency of stop words that exist in documents causes errors in the processing results.

The syntactic tagging of words is done for two purposes. First, stemming takes place based on the syntactic category of the words. The second reason for the need for syntactic tags is to determine the most frequent syntactic nouns, verbs, and adjectives that exceed the defined threshold. This POS tagger is trained based on the Bijan Khan’s data. It works based on the Markov's hidden modeling method, and divides words into specified categories of nouns, verbs, adverbs, prepositions, adjectives, conjunctions, conditional words, pronouns, nouns, and punctuations.

3.3. Cognitive Linguistic Features

Once a suitable corpus for processing was prepared and normalized, it was time to extract the linguistic and statistical properties in order to train the classification algorithms. The cognitive linguistic topics were used in order to identify the appropriate linguistic features.

The scientific study of the mind and its related processes are known as the cognitive science, which attempts to study the nature, roles, and actions of the mind. The researchers in this field are trying to study the human intelligence and behavior by focusing on how neurons display and process the information. The famous American psychologist Ekman has divided the human emotions into the general categories of anger, fear, sadness, happiness, surprise, and hatred [24]. He has defined traits for each emotion that distinguish it from the other emotions. For the linguistics researchers, for each one of these emotions, language reflects patterns of the thought and features of the human mind. These concepts are expressed as the conceptualized patterns, i.e. language presents a person's mental concepts in a dynamic way using the symbolic elements such as the syllable, word, sentence, and context. While using a language, the humans try to express their complex subjective content in a more objective and accessible format.

If there is a direct or indirect relationship between the emotion and the language, how is this relationship displayed? This relationship can well be summarized in this way:

Emotion language:

- Expressive
- Descriptive
    - Literal
        - Basic
        - Non-basic
    - Figurative
        - Metaphor
        - Metonymy

Words like "oh", "hooray", and "wow" in context show sadness, joy, and surprise, respectively. These words are called the expressive words [25]. These words represent the meaning of emotion within themselves but do all feelings always appear in this way? Another set of words that describe the feelings are called the descriptive words. Words like "anger", "happiness", and “wonder" are descriptive words. Among the descriptive words, not all words are equally important, and some are better examples and count in the emotion prototype. These words are known as the basic words, and another group is called the non-basic words.

According to the words people use in order to express their feelings directly and indirectly, the emotional concepts are divided into the literal and figurative terms. If the meaning of construction is not obvious at the first look, and its meaning is implicit, then this construction is called the figurative term. The discussion of abstractness of feeling is expressed by a figurative speech. One of the abstract features of the figurative speech is the frequent use of metaphors. For example, feeling of anger in the sentence "He exploded out of anger" is considered as a hot liquid inside the container. The conceptual metaphors relate the two domains in terms of some common features they have. One area is usually more objective and more tactile than another. In addition to the emotional metaphors, the metonymy concepts are also used to express one's feelings. In this case, unlike metaphors, it does not relate to two domains, and only represents one domain. Its purpose is to provide a mental access to a particular domain through a part of the same domain or it tries to relate to another part of the same domain using one part of a particular domain. For example, anger is a characteristic of an increase in the body temperature so when the person turns red, it indicates the facial structure of the person's physical state.

According to what is known in the cognitive sciences about emotion and how feeling is represented by language, several perspectives can be examined assuming that there is a relationship between emotion and language and hatred [26]. The first view is that which words can show the internal emotion of persons. The second view is how the emotional terms are expressed at the phonetic, lexical, syntactic, semantic, and contextual levels of the language. The third view is that which constructions show the personal emotion. Thus the features used in the proposed system are as follow:

- Emotional keywords
- Emotional syntactic categories
- Emotional constructions

Since some of the contextual sensations are implicit, the meaning of the words is specified in the context; in this work, it is attempted to examine them using the internal word embedding and neural networks.

3.3.1. Emotional Keywords

People, depending on how they feel, use different words in different situations. For example, the words people use when they are angry are different than the words they use when they are happy. The expressive and literal words were analyzed in this part. Thus a list of semantic keywords associated with each emotion was provided. In order to compile the keyword list, the Persian lookup table lexicon containing a list of 2,947 words was used [27]. At the end, about 350 words with emotional semantics were identified as a list of keywords of the 2,947 words that were available. Based on the human judgment, two linguists have selected the words that have the most relationship with the emotional texts and have a high frequency in the texts. Then the prepared keywords were examined to which category of emotion they belonged. The presence or absence of these words was considered as a feature of the system. Some of the top emotion-related keywords in the Persian language are presented.

- Anger: “خشم”, “عصبانیت”, “داد”, “غضب”
- Sad: “غم”, “غصه”, “بغض”, “اندوه”, “ماتم”
- Happiness: “شادی”, “خوشحالی”, “خنده”, “ذوق”
- Fear: “ترس”, “رعب”, “وحشت”, “اضطراب”
- Surprise: “حیرت”, “تعجب”, “مات”, “مبهوت”

This linguistic attribute is shown by relation (1). For each emotional tag $\{1...S\}$, if the syntactic role associated with the emotion within the given data was found in document, it equals 1; and else, it equals 0.

$$\text{D}=\begin{cases} 1 \ \ if \ \ S(w)=1 \\ 0 \ \ \ Otherwise \end{cases} \tag{1}$$

3.3.2. Emotional Syntactic Categories

The other features of the system studied include the syntactic roles of nouns, adjectives, adverbs, and verbs that occur in terms of the type of emotions perceived in the text. In writing, people try to express what they are feeling by using specific words. For example, the specific names such as "shout" and "anger", and the specific actions such as "scream" appear more often in the texts expressing anger.

At first, all the prepared documents were labeled by POS tagger. This POS tagger was provided based on the hidden Markov’s model on the corpus of Bijan Khan. In this way, a list of high-frequency syntactic roles was prepared in order to serve as one of the linguistic features of emotion recognition. The criterion for selecting these syntactic roles is the frequency of these words, which exist in the emotional corpus. By setting the threshold for each group in terms of frequency, the items that were more were considered as syntactic maps related to a particular emotion.

Table 2 shows some of the top emotion-related syntactic roles in the Persian language. This syntactic attribute is also shown by relation (1).

Table 2. Samples of emotional syntactic roles

Emotional text	Adjective	Noun	Adverb	Verb
Happiness	خوشحال	نشاط	خنده آوری	قهقهه زدن
Sadness	ماتم زده	غصه	افسوس وار	گریه کردن
Angry	خشمگین	عصبانیت	وحشیانه ای	کتک زدن
Fear	مضطرب	بیم	دلهره آور	ترسیدن
Surprise	متحیر	تعجب	عجیبی	ماتش بردن

3.3.3. Emotional Constructions

In addition to the uncertain boundaries that exist in the type of emotion, and in addition to the relative complexities that exist in their structures, another feature that is examined from the cognitive view point is the discussion of the abstraction of emotion using the metaphorical and contextual structures. The subject of abstraction becomes even more challenging as the researchers wish to identify and process the emotional constructions automatically. However, by the use of Persian idioms dictionary [28], it was attempted to make a list of the metaphorical and contextual structures used to express a particular emotion. This book contains the Persian construction terms along with various examples from different texts, especially Persian fiction. In order to study the emotional structures more comprehensively, the studied structures have also been used in the articles that have studied emotional metaphors in the Persian language. All stages of selecting the emotional structures are based on the opinions of the linguists. A list of more than 600 types of emotional constructions was prepared. The presence of these structures was considered as a feature in order to identify the feeling expressed in the texts. This feature has been shown the same as the other two features by relation (1).

There are common emotional structures between different languages. For example, for “flying in the clouds”, there is also an emotional structure like this: “روی ابرها پرواز کردن” in the Persian language. However, some structures are unique to that nation due to their relationship to the culture and nationality. These subjects make it necessary to examine these emotional structures. Thus this feature is language-dependent and requires a specialized study of the Persian language.

Since the emotional structures do not have fixed structures and other words may be placed inside these structures or the words within these structures may be pushed back and forth, when identifying them in the text, the presence of the main words of these structures in the text was examined. In sentences such as “ نفسش از ترس بند آمدن”, the words “از ترس” are placed between the emotional structures of fear. In structures such as “قند تو دلش آب شدن”, words of structure can move inside the main structure like this “ تو دلش قند آبشدن”. Thus in order to examine this feature, it was discussed whether there are main words of structure or not. Some prototypical samples of emotional structures have been shown at the bottom.

Sample of emotional constructions:

- Happiness
  - کبکش خروس خودندن
  - قند تو دل آب شدن
- Anger
  - از کوره در رفتن
  - برق از چشم پرید
- Sadness
  - دل آدم کباب شدن
  - مثل ابر بهار اشک ریختن
- Fear
  - زهره ترک شدن
  - نفس بند آمدن
- Surprise
  - شاخ درآوردن
  - چشم گشاد شدن

3.4. Embedding Layer

There are words in the language that have the same pronunciation and text but have different meanings in accompanying with other words. These words are called the polysemous words. The word “Shane” is an example of these words by the meaning of “comb”, “shoulder”. This information and other linguistic information need to be converted into numerical information for being analyzed by the computer. On the other hand, learning machines are not able to apply raw information very well so the numeric word vectors help to extract and discover this linguistic information and patterns that exist within the texts.

Since the vectors created by the term frequency-inverted document frequency represent only a frequency range of words, and are not able to represent the relationships between words, it was decided to display the embedding vectors of Word2Vec [29]. The advantages of this method are cases such as representing reduced volume vectors, predicting the neighboring words, and adding new words and sentences into the data. It captures a set of large datasets and then represents them in space vectors of several hundred directions, i.e. for each word within the data, it produces equivalent specific features in space. These vectors also find the ability to predict synonyms, antonyms, neighboring, and other semantically-related words. Due to the complexity of the language, this kind of word embedding is efficient for being used in the NLP tasks.

The general purpose of using lexical vectors is to obtain high-quality vectors from a large volume of data. Skip-Gram and continuous bag of words are two well-known methods that are used for word-embedding from the original texts. Continuous bag of words was selected for embedding of words in this paper. The vector length considered for each word was assumed to be 100. For each document, a vector was made of the average vector length in the document.

3.5. Gated Recurrent Unit

One of the most important and modern topics in the computer science is neural networks that are used in the fields of image, sound, and text. Deep learning is a set of machine learning algorithms that operate on artificial neural networks in order to represent abstract relationships between the data at high levels. The properties of the proposed model can be performed by monitoring the labeled data as well as the raw data. The main feature of this method is having multiple layers of processing with non-linear operations in the implementation of algorithms. The general approach of this method is to be trained with a set

of data, and then it predicts the new data. The learning process in this model is reciprocal. The reciprocal process means that it identifies the variables involved in order to predict the new data simultaneously using the data that is used as the training data. Then when other training data is processed, it checks for how many errors the selected variables have. The result obtained is fed back to the model until the error value is reduced and the model based on multiple variables can increase the prediction accuracy of the new data. This process continues until the error rate is reduced.
Gated recurrent unit has been introduced in 2014 by Cho *et al*. [30]. It is generally regarded as a modified version of LSTM because both architectures use a similar design. The architecture was designed to address the shortcomings of the traditional recursive neural network such as the gradient fading problem found in LSTM. This type of architecture uses the concepts called the update gate (z_t) and reset gate (r_t). These two terms are the gates of the two vectors that decide whether or not to transfer information to the output. The special thing about these gateways is that they can be trained to retain information without having any change over time during different time steps. The GRU recursive neural network uses a new concept called the update gateway in order to store information over time. The reset gateway essentially acts like a switch, whereby the network can determine how much information is not required in the current step and how much the previous step information is used in the current step. With these two new features, the GRU neural network can easily store or filter information from the previous steps. In this way, it eliminates the shortcomings of the traditional recursive neural network. W and b in (2), (3), and (4) correspond to the weights and biases for the gates.

$$r_t = \sigma(W_{ir} x_t + b_{ir} + W_{hr} h_{(t-1)} + b_{hr}) \quad (2)$$

$$z_t = \sigma(W_{iz} x_t + b_{ir} + W_{hz} h_{(t-1)} + b_{hz}) \quad (3)$$

$$n_t = \tanh(W_{in} x_t + b_{in} + W_{hn} h_{(t-1)} + b_{hn}) \quad (4)$$

$$h_t = (1 - z_t) n_t + z_t h_{(t-1)} \quad (5)$$

The set of hyper-parameters used in this paper are an embedding size of 100 and a weighted dropout of 0.2. The model has been trained for the 15 epoch size using batch a size of 64. The softmax activation and loss function of "categorical_crossentropy", and Adam optimizer are used in this model.

3.6. Dropout and Dense Layer

Over-fitting is a serious problem that usually occurs in the deep learning method [31]. A regularization technique known as dropout will be used to avoid this problem. Over-fitting usually occurs as the amount of training data is not very large, randomly dropping some units of neural networks along with their connection improve the performance of the system for not being over-fitted. A dropout of 0.2 between the GRU layer and the dense layer was applied in this work.
After feature extraction in the last steps, the fully connected layer was used to present the network result in a vector of a specified size. A dense layer of 5 was used for the proposed model. It works based on which feature in the previous layer most correlate to a particular class.

3.7. Classification

Machine learning is a sub-division of the computer science that enables the computer to be able to learn without being explicitly trained. The structural study of algorithms that can learn and predict using the available data falls within its scope. After the training data was provided with appropriate labels, the type of feeling classified was determined by the classification algorithms. The classification algorithms used in this section include, Naïve Bayes, SMO support vector machines, and decision tree j48.

4. Experimental Results

After the classification algorithms were implemented on the prepared training data, then a 10-fold cross-validation method was used in order to evaluate the performance of the system. By default, the algorithm divides the data into ten sections, each examining one section as the test data and the other nine sections as the training data. The method of calculating the precision, recall, and accuracy of the readings is presented below in Equations (6), (7), and (8).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (6)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (7)$$

$$Accuracy = \frac{All\ True}{All\ True + All\ False} \quad (8)$$

Initially, each feature was evaluated in the classification algorithms in order to determine the precision and recall of each feature alone. Table 3 shows the results obtained from the precision, recall, and accuracy of each feature for different classification algorithms.

Table 3. Results obtained from different features

	Deep learning feature (F1)			Cognitive feature(F2)			F1+F2		
	P	**R**	**A**	**P**	**R**	**A**	**P**	**R**	**A**
Svm	87	87	94	85	82	92	93	93	97
Naiive bayes	87	87	94	81	80	92	90	90	95
Decision tree j48	85	85	93	79	79	91	92	92	96

Since the SVM algorithm has obtained the best result, it was chosen as the default algorithm for emotion detection. In the following, we examined the precision and recall of different classifiers in identifying each emotion separately. Table 4 shows the results obtained by the SMO algorithm for each feature.

Table 4. Accuracy obtained by SMO algorithm for each feature.

Emotional text	Features			
	Deep learning	**Keyword**	**POS**	**Construction**
Happiness	95	90	85	72
Sadness	93	90	81	79
Anger	95	86	85	81
Fear	93	94	89	83
Surprise	95	94	90	93

5. Conclusions and Future Works

This work was a dual-purpose research work in the field of cognitive sciences and new deep learning methods in order to show that the study of linguistic properties is very important for the purposes of language processing. It is not enough just to examine the statistical methods for language processing. In the field of humanities, it also shows that in the modern age, the use of statistical science is very helpful in studying the underlying parts of the language. For example, deep learning has been the subject of much attention in the recent years, and with its neural networks, it has been working to design a neural network similar to the human brain. Finally, the results of this work indicate that it is useful to study the cognitive properties along with the neural networks. Compared to the other two proposed methods, each of which focus on the cognitive or statistical sciences alone, the third method has achieved a higher degree of system performance by combining the features expressed by the two sciences.

In this work, it was attempted to classify the feelings of sadness, happiness, anger, hatred, and fear for the Persian language. Analyzing several cognitive features of human language and the statistical features were the other points studied. Although there was a scarcity of Persian resources for evaluation of data mining, it was attempted to provide an appropriate corpus of emotions in order to evaluate and analyze the proposed system. The results tabulated in Table 3 show the performance level of the proposed features used in this work for different algorithmic classifications. The results obtained showed that the combination of the cognitive and statistical features resulted in a high accuracy compared to when these features were used individually. Another point that can be seen from the table is that neural networks are able to show the semantic relationships between words, and their results are reliable for the future studies.

The results shown, in Table 4 show that each one of these features has an important effect on detecting the emotions. The features obtained by the GRU neural networks and emotional keywords play an import role in data mining of this work. The results obtained for the POS feature show a good performance of this feature but improving this feature in future studies can be effective. It should be noted, however, that emotional structures are difficult to identify and process due to the complexity of their language processing and further investigation in this domain; however, they will improve the performance of the system. Analyzing emotional construction in more details will be included in the future research work.

At the end, using other cognitive and statistical features in this area can be effective in improving the system performance. Studying other textual areas in Persian is also an important task that is useful in expanding the system performance.

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Appendix A

Stop words

به	امروزه	بعدا	كاملا	حال
با	امشب	بعداً	مگر	حتما
بر	تا	بعدازظهر	آن كه	حتماً
در	يا	بعضي	نمي	حتي
که	این	بعضي شان	نه	حداقل
و	را	بعضيها	نه تنها	حداكثر
یا	آن	بعلاوه	نهايتا	حدود
یک	مانند	بلافاصله	ها	در باره
دو	و	بلكه	هاي	دو روزه
سه	--	بله	هايي	دوباره
چهار	!	بنابراين	هر	علاوه بر
پنج	"	پريروز	هر از گاهي	علاوه بر آن
شش	#	پس	هر چند	علناً
هفت	(	پس از	هر چند كه	علي الظاهر
هشت	)	پس فردا	هر چه	علي رغم
نه	*	تعدادي	هرچند	عليه
ده	.	تعمدا	هرچه	عموم
است	...	تقريبا	هركس	عموما
بود	....	تقريباً	هرگاه	عموماً
شد	/	تك تك	هرگز	عنقريب
گشت	:	تلويحاً	كجا	عيناً
گردید	[	جز	درباره	فر
هم	]	جلو	درحالي كه	فردا
همینطور	،	جلوي	بعضيهايشان	فعلاً
اکنون	؛	بعدها	چند	فقط
الی	؟	كاش	چه	فلان
اما	«	كاشكي	چون	كاش
امروز	»		چيز	

شناسایی احساس در متون فارسی با استفاده از ویژگی‌های زبان‌شناختی و الگوریتم‌های یادگیری ماشین

سیده ساره صادقی[۱]، حسن ختن‌لو[۲،*] و محمد راسخ مهند[۳]

[۱] دانشکده ادبیات و علوم انسانی، دانشگاه بوعلی سینا، همدان، ایران .

[۲] گروه مهندسی کامپیوتر، دانشکده مهندسی، دانشگاه بوعلی سینا، همدان، ایران.

[۳] دانشکده ادبیات و علوم انسانی، دانشگاه بوعلی سینا، همدان، ایران.

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چکیده:

بسیاری از منابع نوشتاری که امروزه به‌طور چشمگیری در حال افزایش هستند در ارتباط با نظرات و احساس‌های کاربران است. تحلیل و واکاوی این نظرات در سال‌های اخیر توجه زیادی را به خود جلب کرده است. بدین ترتیب در این پژوهش به معرفی سامانه‌ای شناسایی احساس پرداخته‌شده است که برحسب ویژگی‌های زبان‌شناسی شناختی و روش آماری یادگیری عمیق طراحی‌شده است. در ابتدا پیکره احساسی به میزان ۲۳ هزار سند از پنج احساس اصلی غم، شادی، خشم، ترس و حیرت تهیه گردید. سپس ویژگی‌هایی همچون کلمات کلیدی احساسی، مفاهیم احساسی و نقش‌های نحوی مرتبط با احساس به‌عنوان ویژگی‌های شناختی مطرح گردید. همچنین پس از آزمایش‌های گوناگون شبکه عصبی واحدهای بازگشتی مبتنی بر دروازه به‌عنوان بخش آماری کار مورداستفاده قرار گرفت. بدین ترتیب با استفاده از نرمال‌سازی متن، بردارهای واژگانی با الگوریتم Word2Vec تعبیه شد و به‌عنوان داده ورودی در شبکه‌های عصبی مورداستفاده قرار گرفت. توجه به حضور یا عدم حضور ویژگی‌های زبان‌شناختی و نتایج به‌دست‌آمده از روش یادگیری عمیق به‌عنوان ویژگی‌هایی در الگوریتم‌های دسته‌بندی کننده نایوبیز، درخت تصمیم و بردارهای پشتیبانی ماشین قرار گرفت. در بخش انتهایی نیز با استفاده از ارزیابی متقابل به بررسی میزان عملکرد سامانه پرداخته شد و میزان صحتی برابر با ۹۷٪ کسب شد. نتایج به‌دست‌آمده بهبودی چنددرصدی را در مقایسه با هنگامی‌که هر یک از ویژگی‌های زبان‌شناختی و آماری جداگانه مورداستفاده قرارگرفته بودند نشان می‌دهد. توجه به ویژگی‌های دیگر بکار رفته در این زمینه و بررسی ویژگی‌های شناختی در سطوح عمیق‌تر در بهبود عملکرد سامانه مؤثر خواهد بود.

کلمات کلیدی: زبان‌شناسی شناختی، یادگیری ماشین، یادگیری عمیق، سامانه شناسایی احساس، ارزیابی متقابل.