Intelligent Methods in Engineering Sciences 3(1): 007-012, 2024

INTELLIGENT METHODS
IN ENGINEERING SCIENCES

https://www.imiens.org

International Open Access

March, 2024

e-ISSN 2979-9236

Research Article

https://doi.org/10.58190/imiens.2024.82

Emotion Detection with Pre-Trained Language Models BERT and ELECTRA Analysis of Turkish Data

Abdulkadir TEPECIK [a,*], ***Engin DEMIR*** [b]

[a] *Computer Engineering Department, Yalova University, Yalova, 77200, TURKIYE*
[b] *National Defense University, İstanbul, 34353, TURKIYE*

ARTICLE INFO

Article history:
Received 29 January 2024
Accepted 09 March 2024

Keywords:
BERT,
ELECTRA,
Language Models,
Transformer,
Turkish Sentiment Analysis

ABSTRACT

Developments in artificial intelligence have led to positive developments in many fields. Sentiment analysis, one of these areas, has become more applicable with the models and architectures developed. In this study, emotion detection and emotion analysis were performed on the transcribed data of Turkish voice recordings. In the emotion detection phase, after the emotional states (positive, negative, neutral) of the data were detected with BERT and ELECTRA models, which are transformer-based structures, machine learning algorithms were used in the accuracy analysis of these emotional states and the Google Colaboratory platform was used in the application phase. Naive Bayes, Random Forest, Support Vector Machine and Logistic Regression algorithms were used in the accuracy analysis. As a result of the study, both Naive Bayes and Logistic Regression algorithms achieved the best accuracy rate in emotion detection with the BERT model with a rate of 70%. In emotion detection with the ELECTRA model, both Random Forest and Logistic Regression algorithms achieved the best accuracy rate of 72%. BERT and ELECTRA methods are used to provide a better understanding of understanding and classification of emotional content in Turkish texts and contribute to the development of sentiment analysis-based applications. In addition, two Turkish emotion data sets were obtained, and by using more than one method in emotion analysis, our study has been a unique study in the field, allowing the analysis of the study to be done more effectively.

1. INTRODUCTION

The development of technology has enabled advantages and innovations in every field, as well as many facilities in research related to people. One of these research topics is research into people's emotions. Emotion detection and analysis have allowed to obtain ideas about individuals on many issues.

People are able to express their emotions both through body language and through the sounds in speech. In cases where body language is insufficient, emotions are transmitted through the sounds in speech. The detection and analysis of emotion in sound has been quickly applied with the science of machine learning, which makes data analysis more practical today, and has allowed successful results.

In the study, which was analyzed on the texts obtained from the sounds in public databases and videos, it was aimed to improve the search engines and users' ability to search for relevant information. Hidden Markov and Support Vector Machine algorithm were used in the study. In the conclusion, it is stated that the study reveals open-ended analyzes and brings about many controversies related to this [1]. The study, which presented an approach to perform sentiment analysis on a dataset containing news videos, focused on the tension of news and the intelligibility of emotions. In the conclusion, it was stated that the approach provided high accuracy in news videos with high tension, but the same success rate could not be achieved in videos with low tension [2].

In the study, an automatic emotion recognition system was proposed to obtain people's emotions from auditory information, and features were extracted from the audio signals in these datasets using SAVEE, RAVDESS and RML datasets and a deep learning-based LSTM algorithm was used for classification. In the conclusion, it was stated that the most successful results were obtained for the SAVEE data set and this was due to the fact that the SAVEE data set was obtained from male speakers whose native language was English [3]. Presenting a new approach to the emotion identification system using sounds from human speech, the study tried to provide estimates of four types of emotions (angry, sad, happy and neutral) and used the Berlin emotion database in this

*** Corresponding Author:** atepecik@yalova.edu.tr

context. In the conclusion of the study, which used machine learning algorithms to classify Neural Networks and Support Vector Machine, it was stated that the approach with a relative frequency coefficient of one thousand gave promising results [4].

In the study aiming to detect and classify emotions in speech, using EmoDB and RAVDESS data sets, Mel Frequency Cepstrum Coefficient properties in speech were extracted and Logistic Model Tree models were trained using these features. In the conclusion of the study, it was stated that the accuracy rate in the detection of 7 different emotions was 70% and that the contextual information in speech signals should be removed for future studies [5].

In the study that proposed a voice emotion recognition model, it was aimed to find the best among the classification algorithms, which are an important factor in sentiment predictions, with this proposed model. In the study, RAVDESS dataset was used and K-Nearest Neighbor, Support Vector Machine, Random Forest and Decision Tree classification algorithms were applied on this data set. In the conclusion, it is stated that according to the evaluation made according to the complexity matrix, the Random Forest classification algorithm gives the best result [6]. To detect emotions in speech, a hybrid model is presented. With the proposed hybrid model, a differentiating model structure used for temporal productivity and classification was established. It is stated in the conclusion that this model, which is applied on AVEC, VAM and SPD data sets, provides a superior classification performance with the contribution of CRF, which enables the modeling of temporal dependencies [7]. It is aimed to analyze both the speech and the corresponding text component in order to detect the emotions of the speaker. The proposed method is aimed at improving the efficiency of emotion classification by combining the properties of both audio and text into a single feature vector, which is then given to the classifier. In the study, Semval-2007 and eNTERFACE'05 EMOTION datasets were used with methods such as natural language processing, Support Vector Machine, WordNet effect and SentiWordNet. In the conclusion of the study, it was stated that the proposed method provided better accuracy compared to text mining or speech mining, and its accuracy was significantly higher compared to voice or text classification alone [8]. In the study, which aims to determine the emotional situation using voice data, it is aimed to develop a system specific to Turkish. In the study, a data set consisting of 2194 records of anger, sadness, excitement, happiness, helplessness and neutral emotions was created and various classification algorithms were used. In the conclusion of the study, it was stated that as a result of experiments on data sets, the Random Forest algorithm obtained better results [9]. In the study, which aims to analyze the effects of emotions on sound and the results using machine learning techniques by using the international emotional digital sound dataset, Regression models and Artificial Neural Network models from machine learning methods were used. In the conclusion, it is stated that the Artificial Neural Network model shows better results than Regression models [10]. It is intended to conduct an experimental study to recognize emotions from human speech. In the study, which took into account neutral, anger, joy and sadness feelings for the experiments, a data set was created over 30 subjects. After the classification of emotions, it was stated in the conclusion of the study that instead of considering the data obtained from a group of people, the data collected from one person should be taken into account [11]. BERT, ELECTRA and ALBERT models were used in the sentiment analysis performed using the product comments on the hepsiburada platform. Random Forest, Naive Bayes and Logistic Regression machine learning methods were also used to analyze the results. In the conclusion of the study, it was stated that the model that provided the highest accuracy rate among the language models was ELECTRA and that the Naive Bayes algorithm achieved the highest accuracy rate among the machine learning algorithms [12]. In the study, which carried out sentiment analysis of user comments on different topics in Turkish language, BERT model was used in the analysis part. BERT was first used for Turkish comments, then translated into English for user comments and another version of the BERT model was used. In the conclusion of the study, it was suggested that better results were obtained in the translated interpretations and that improvements could be made in the BERT model for the Turkish language [13]. A comparison of language models and a new text filtering method for sentiment analysis in Turkish has been made. BERT, ALBERT, ELECTRA and DistilBERT methods were used in the study. As a result of the study, all of the language models applied text filtering methods achieved an accuracy rate above 90%, while the ELECTRA-Tr language model achieved the best performance with a rate of 98.38% [14]. In the sentiment analysis performed on Covid-19 tweet texts, BERT, RoBERTa and BERTweet methods were used together with Naïve Bayes algorithm. It was reported that BERT-based models achieved a 90% success rate and the BERTweet method achieved the best result with a score of 91% [15]. Supervised machine learning methods were used to predict the emotions expressed through texts on social media. SVM, RF, DT, LR and KNN classifiers were used to classify texts as positive, negative and neutral. As a result of the study, it was reported that SVM and RF performed better than other methods [16].

With this study conducted with the data obtained from Turkish voice recordings, it is aimed to create a Turkish sentiment data set, to determine the success of the analysis of BERT and ELECTRA models on Turkish data and to pioneer the studies to be carried out with this model structure and to determine the success rates of machine learning algorithms in Turkish data.

2. Materials and Methods

In this part of the study, the data set, BERT and ELECTRA models used for emotion detection and machine learning algorithms used for analysis are included.

2.1. Dataset

The dataset is taken from the Common Voice platform, which was developed to create a free database for voice and speech recognition software launched by Mozilla. On this platform, there are voice recordings for various languages and text documents of these voice recordings, which were created to teach machines how people speak. The 592 MB file containing Turkish voice recordings contains Turkish voice recordings contains approximately 20,760 audio data. The contents of the audio recordings are; audio from news videos and recordings made on the platform. The information for this data set is given in Table 1.

Table 1. Age and rate information for the data set

Age Rate	Rate (%)
Less than 19	4
Between 19-29	47
Between 30-39	23
Between 40-49	3
Between 50-59	1

For this data set, a gender ratio of 71% male and 6% female was also shared. All the text documents of these audio recordings, many of which consist of repetitive recordings, have been combined. Sieving was performed on the obtained text documents. After parsing the meaningless, repetitive and number-only data were obtained, 5001 pieces of text data were obtained.

This data set has been made ready for emotion detection and analysis processes that constitute the content of the study after the separation of meaningless data. In the practical parts of the study, part of the dataset was used for testing. As a result of the proportioning experiments conducted on the data set, the test data set rate was determined as 15%.

2.2. BERT

BERT (Bidirectional Encoder Representations from Transformers) is a new method of pre-training language representation that achieves the most advanced results on a wide range of natural language processing tasks. Developed by Jacob Devlin and colleagues at Google in 2018, this model structure evaluates the sentence from both right to left and left to right. Thus, it better reveals the relationship of words to each other. The structure of the model includes the BookCorpus and Wikipedia datasets [14]. The BERT model structure is given in Figure 1.

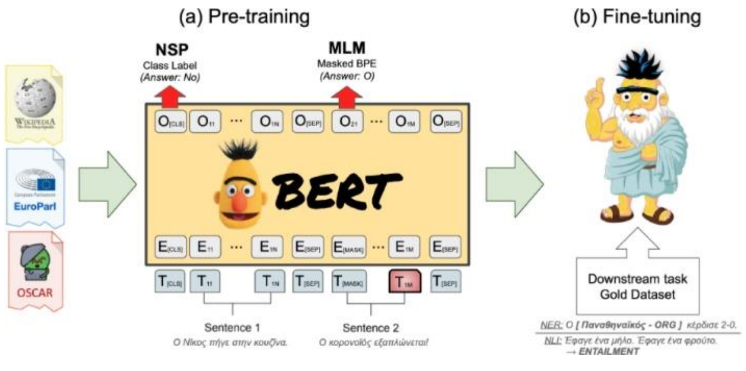

Figure 1. BERT model structure [14]

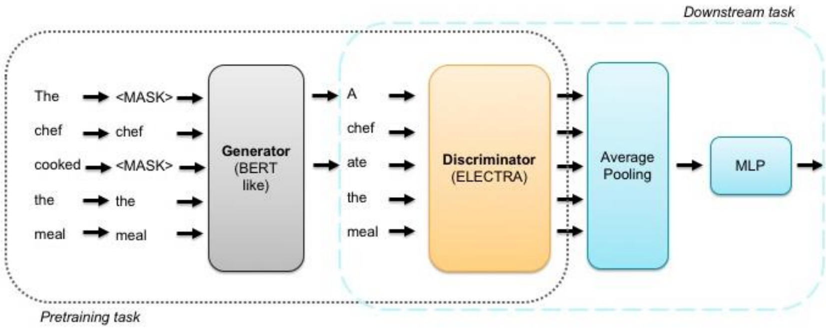

Figure 2. ELECTRA model structure [16]

The examination of the text document given the BERT model structure from both the right and the left provides a better learning at the training stage with the methods in the structure.

2.3. Electra

ELECTRA (Efficiently Learning an Encoder that Classifies Token Replacements Accurately) is used to pre-train transformer networks using less computation than BERT [15]. ELECTRA offers the modified token detection task for language model pre-training to distinguish actual input tokens from bad tokens. The ELECTRA pre-training task has been shown to perform well on various data such as language, etc.

Instead of masking the input in this approach, it distorts it by replacing some icons with similar values sampled from a small network of generators. Then, instead of training a model that predicts the original values of the corrupted symbols, it has a discriminatory model structure that predicts whether each icon in the bad input has been replaced with its instance in the generator [16].

2.4. Naïve Bayes

The Naive Bayes (NB) algorithm is a learning algorithm based on Bayes' theorem. Although it has a lazy structure, it can also work in irregular data sets. The NB classification algorithm is the product of all conditional probabilities [17]. This algorithm is used in spam filtering, sentiment analysis, multiclass forecasting, recommendation systems, and so on [18].

2.5. Random Forest

Random Forest (RF) is a classification algorithm that tries to make the classification process the best by producing models that are more cohesive and produce better results by using the advantages of multiple decision trees. RF is a flexible, easy-to-use machine learning algorithm that often produces a great result. The most important advantage of the RF algorithm is that it can be used in both classification and regression processes [19]. This algorithm can also be evaluated for classifier categorical data. The RF algorithm also addresses over-fitting problems.

2.6. Support Vector Machine

Support Vector Machine (SVM) was derived from statistical learning theory and VC-dimension theory by Vapnik in 1995. SVM was developed to solve the problem of binary classification. SVM is also defined as the ability to process complex data with high accuracy. The main goal in SVM is to find a hyperplane that separates trained data samples into a predefined number of classes [20-21]. The algorithm is also divided into linear and non-linear. In the nonlinear method, the method of kernel functions is used. The SVM algorithm is used in text and image classification, in the fields of biological science, and in areas such as the recognition of handwritten characters [20-21].

2.7. Logistic Regression

Logistic Regression (LR) is a statistical method for predicting binary classes. This method estimates the probability of an outcome that can have only two values. Forecasting is based on the use of one or more predictors. Logistic Regression is often used to predict the class relationships of numerical and categorical variables. This algorithm is used in data mining, learning applications, and classification models [22].

2.8. TF-IDF and CountVectorizer

For machine learning in computers, data needs to be transformed into vectorization processes, that is, numerical data. In our study, TF-IDF and CountVectorizer methods that perform vectorization processes were used.

The method that calculates the values of each word in a document with the frequency of the word in a particular document and the percentage of documents in which the word appears is called the TF-IDF vectorization method. Terms that frequently occur within the document become dominant within the document and take precedence over other terms. To avoid this situation and to produce solutions, the TF-IDF vectorization method is used [23]. The TF-IDF method is used in operations such as filter stop words, text classification.

$$w_{i,j} = tf_{i,j} x \log \frac{N}{d_{f\,i}} \tag{1}$$

$tf_{i,j}$: The frequency with which the word i appears in document J

$d_{f\,i}$: Number of documents containing the word i

N : total number of documents

The CountVectorizer converts a collection of text documents into a matrix of token numbers. This vectorization method, which also processes texts before vector representation, also increases the functionality of the text [14]. The CountVectorizer method is used especially effectively in text classification and analysis.

The most basic difference between these two methods is expressed as follows; In CountVectorizer, even if the term appears in different documents, it indicates the amount of that word in the matrix. The purpose of TF-IDF is to highlight words that are common in a document but not in a document. These two methods were applied separately in each algorithm. Among the results obtained, they contributed to different evaluations.

3. Experiments and Results

In the application part of the study, firstly, the emotional states of 5001 data were determined. Emotional states were determined by BERT and ELECTRA models and these emotional states were determined as positive and negative. After the mood detection with the BERT model, data with 2956 negative and 2045 positive emotion labels were obtained. There are proportionally 59% negative and 41% positive sentences in the data set. Some of the output results are given in Figure 3.

After the mood detection with the ELECTRA model, data with 1578 negative and 3423 positive emotion labels were obtained. There are proportionally 31.5% negative and 68.5% positive sentences in the data set. Some of the output results are given in Figure 4.

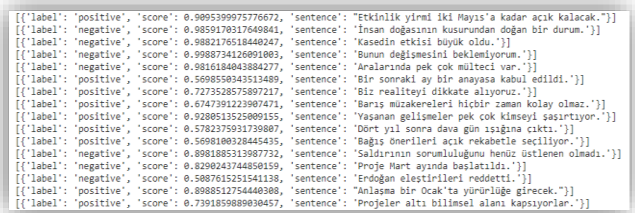

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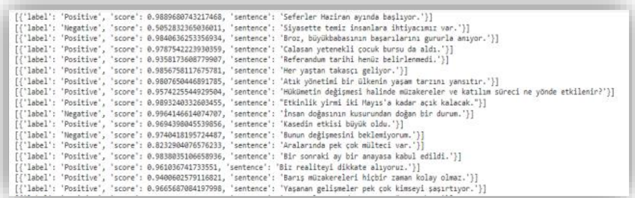
Figure 3. Emotion detection results with the BERT model.



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[{'label': 'Positive', 'score': 0.9807650446891785, 'sentence': 'Atık yönetimi bir ülkenin yaşam tarzını yansıtır.'}]
[{'label': 'Positive', 'score': 0.9574225544929504, 'sentence': 'Hükümetin değişmesi halinde müzakereler ve katılım süreci ne yönde etkilenir?'}]
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[{'label': 'Negative', 'score': 0.9740418195724487, 'sentence': 'Bunun değişmesini beklemiyorum.'}]
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[{'label': 'Positive', 'score': 0.961036741733551, 'sentence': 'Biz realiteyi dikkate alıyoruz.'}]
[{'label': 'Positive', 'score': 0.9400602579116821, 'sentence': 'Barış müzakereleri hiçbir zaman kolay olmaz.'}]
[{'label': 'Positive', 'score': 0.9665687084197998, 'sentence': 'Yaşanan gelişmeler pek çok kimseyi şaşırtıyor.'}]
```

Figure 4. Emotion detection results with the ELECTRA model.

Analyses were performed on the data with the most widely used machine learning algorithms in the literature in this field. In the analyzes; Naive Bayes, Random Forest, Support Vector Machine and Logistic Regression algorithms were used. In the analysis conducted through the Python programming language, CountVectorizer and TF- IDFVectorizer methods were used to digitize words. In the results of the analysis, accuracy, nominal value, sensitivity value and f1-score metrics were evaluated. All machine learning algorithms were applied on the outputs of the BERT and ELECTRA models. The data set is divided into 85% training data and 15% test data. The analyses were performed on the test data set. The results of the analysis in Table 2 given below are given.

Table 2. Accuracy Rate Results Achieved with BERT and ELECTRA

Algorithms	BERT		ELECTRA	
	Accuracy			
	CountVec	TF-IDF	CountVec	TF-IDF
NB	%70	%68	%70	%70
RF	%67	%67	%72	%71
SVM	%68	%69	%67	%70
LR	%70	%69	%72	%71

When the accuracy rates were examined, the highest accuracy rate in the analyzes performed after the emotion detection performed with the BERT model was obtained by Naive Bayes and Logistic Regression algorithms with the CountVectorizer method. In the analyzes performed after emotion detection with the ELECTRA model, the highest accuracy rate was obtained by Random Forest and Logistic Regression algorithms with CountVectorizer method.

Table 3. Results of Precisions Obtained with BERT and ELECTRA

Algorithms	Data Emotion Status	BERT		ELECTRA	
		Precision			
		CountVec	TF-IDF	CountVec	TF-IDF
NB	Positive	0.68	0.71	0.74	0.70
	Negative	0.71	0.68	0.54	0.60
RF	Positive	0.69	0.64	0.75	0.75
	Negative	0.66	0.68	0.57	0.56
SVM	Positive	0.63	0.67	0.75	0.76
	Negative	0.70	0.71	0.48	0.52
LR	Positive	0.69	0.71	0.75	0.72
	Negative	0.70	0.68	0.59	0.62

When the results in the sensitivity values were examined, as a result of the BERT model analysis, the Support Vector Machine in negative data and the Logistic Regression algorithm in positive data stood out with high results, while as a result of ELECTRA model analysis, Logistic Regression in negative data and Support Vector Machine algorithm in positive data were more successful.

Table 4. Recall Results Obtained with BERT and ELECTRA

Algorithms	Data Emotion Status	BERT		ELECTRA	
		Recall			
		CountVec	TF-IDF	CountVec	TF-IDF
NB	Positive	0.55	0.44	0.86	0.97
	Negative	0.81	0.87	0.35	0.11
RF	Positive	0.42	0.49	0.87	0.86
	Negative	0.86	0.80	0.39	0.40
SVM	Positive	0.56	0.56	0.77	0.81
	Negative	0.76	0.79	0.46	0.44
LR	Positive	0.52	0.45	0.89	0.94
	Negative	0.83	0.87	0.35	0.20

When the results in the nominal values were examined, as a result of the BERT model analysis, the Support Vector Machine in the positive data and the Logistic Regression algorithm in the negative data stood out with the high results obtained, while the Support Vector Machine in the negative data and the Naive Bayes algorithm in the positive data obtained better results as a result of the ELECTRA model analysis.

Table 5. F1-Score Results with BERT and ELECTRA

Algorithms	Data Emotion Status	BERT		ELECTRA	
		F1-Score			
		CountVec	TF-IDF	CountVec	TF-IDF
NB	Positive	0.61	0.54	0.80	0.81
	Negative	0.75	0.76	0.43	0.19
RF	Positive	0.52	0.56	0.81	0.80
	Negative	0.75	0.73	0.46	0.46
SVM	Positive	0.59	0.61	0.76	0.78
	Negative	0.73	0.75	0.47	0.48
LR	Positive	0.59	0.76	0.81	0.82
	Negative	0.76	0.55	0.44	0.30

When the results in the F1-Score metric were examined, as a result of the BERT model analysis, Naive Bayes in positive data and Logistic Regression algorithm in positive data stood out with high results, while as a result of ELECTRA model analysis, Support Vector Machine in negative data and Logistic Regression algorithm in positive data achieved better results.

4. Conclusions and Future Work

In our study, where emotion detection and emotion analysis were performed on the data set consisting of Turkish voice recording data, Turkish emotion data sets with two emotion labels were obtained, the effect of BERT and ELECTRA models on Turkish data was observed and the performance rates of machine learning algorithms on Turkish data were determined.

The analyses were performed on the Google Colaboratory platform with four machine learning algorithms. Two different vectorization methods were used through the libraries of the Python programming language and more than one evaluation could be made in the results.

In the analyzes made after emotion detection with the BERT model, Naive Bayes and Logistic Regression algorithms were the prominent algorithms in the results obtained with CountVectorizer and Support Vector Machine Logistic Regression algorithms were the prominent algorithms in the results obtained with TF-IDFVectorizer. It can be stated that these two algorithms can be used on Turkish data.

In the post-emotion analysis with the ELECTRA model, Random Forest and Logistic Regression algorithms were more successful in both CountVectorizer and TF-IDF vectorization methods than other algorithms used in the analysis.

In the comparison between BERT and ELECTRA models, it is seen that the ELECTRA model is more successful than BERT. ELECTRA model may be preferred in emotion detection studies on Turkish data.

For future studies to be conducted with BERT and ELECTRA models in Turkish, it can be said that better results will be obtained as a result of improving the Turkish extensions of these model structures. In addition, expanding the data set, model adjustments and using different methods will make positive contributions to the results obtained.

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