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Comparison of Artificial Neural Networks with Dictionary-Based Approach in Aspect-Based Sentiment Analysis

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***Abstract*— In this study, aspect-based sentiment analysis was conducted using both dictionary-based and machine learning approaches. Within the dictionary-based method, three different lexicons were tested, and the highest accuracy rate (87.7%) was obtained with the Turkish-based SentiTurkNet. In the machine learning approach, multi-layer recurrent neural networks (RNN) with GRU units were applied. The best performance was achieved with a three-layer structure, reaching an accuracy rate of 96.12%. Evaluation of precision, recall, and f-score values showed that the developed model successfully classified both positive and negative sentiment poles with high reliability (positive f-score=0.96; negative f-score=0.92). Overall, the findings indicate that while dictionary-based approaches achieve notable results, machine learning-based models demonstrate significantly higher accuracy and robustness.**

Keywords*— *Natural Language Processing, Sentiment Analysis, Aspect-Based Sentiment Analysis, Machine Learning, Dictionary-Based Approach, Educational Institutions Introduction

I. INTRODUCTION

A significant portion of the data we produce today is text-based, which has necessitated the development of various methods and techniques to organize, structure, and make this data meaningful. Processing and making sense of such large volumes of data requires a superhuman capability. At this point, machine learning and Natural Language Processing (NLP) methods and techniques provide essential guidance [1]. Natural Language Processing (NLP), a subfield of artificial intelligence, aims to enable machines to perform communication skills typically attributed to humans—such as expressing themselves using natural language and understanding what others are saying—by leveraging the power of machine learning. One of the most important subfields of NLP is sentiment analysis. The concept of sentiment analysis was introduced into the literature in 2003 with the study "Sentiment Analysis: Capturing Favorability Using Natural Language Processing"[2]. Sentiment analysis involves identifying the emotional states associated with brands, individuals, products, or organizations within textual content using NLP methods [3]. It is fundamentally a classification problem. Sentiment analysis studies are generally conducted at three levels: document, sentence, and aspect (target). In sentiment analysis at the document and sentence levels, the overall sentiment is determined without considering the number of emotional states present in the content. This can result in the loss of sentiment information. Aspect-level sentiment analysis has become a popular approach in recent years. According to this approach, a single text may contain multiple emotional states. In order to determine the sentiment of a text, the targets within the text must first be identified. The sentiment of each target should then be analyzed individually, thereby minimizing the loss of sentiment information. Within the scope of this study, it is aimed to classify user reviews obtained from the website okul.com.tr as positive or negative with high accuracy by using the aspect-based sentiment analysis technique. For classification purposes, both a lexicon-based approach and machine learning techniques—specifically artificial neural networks—have been utilized.

II. LITERATURE REVIEW

The field of sentiment analysis has evolved significantly over the past two decades, with early research laying the foundation for more advanced approaches. One of the pioneering studies was conducted by Pang, Lee, and Vaithyanatham [4], who applied machine learning algorithms to movie reviews. Their experiments demonstrated that Support Vector Machines (SVM) achieved the highest accuracy of 82.9%, highlighting the potential of supervised learning for sentiment classification. With the emergence of social media platforms, particularly twitter, sentiment analysis began to focus on large-scale, real-world datasets. Go et al. [5] collected 1.6 million tweets and tested SVM and Naive Bayes classifiers, reporting accuracy rates between 82% and 83%. Similarly, Pennacchiotti and Popescu [6] employed machine learning techniques on Twitter data to classify users' ethnic and political orientations, demonstrating the versatility of sentiment analysis in different contexts. Subsequent studies adopting machine learning and deep learning techniques achieved notable improvements in classification performance. Matsumoto et al. [7] reported 92.9% accuracy on movie reviews, while Yang et al. [8] achieved 93.5% accuracy on e-commerce data. Furthermore, Pervan and Keleş [9] applied Long Short-Term Memory (LSTM) networks and reached 94.21% accuracy,

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underlining the advantages of recurrent neural architectures. Similar progress has been observed in Turkish sentiment analysis research. Nizam and Akın [10] reported an accuracy of 72.33% on Twitter data, whereas Sevindi [11] achieved an F-score of 0.82 using SVM on Turkish movie reviews. Ayata et al. [12] emphasized the importance of domain-specific sentiment lexicons and demonstrated higher performance in targeted domains. Nassar and Sezer [13] classified Turkish movie reviews using artificial neural networks and obtained an F-score of 0.92. Likewise, Dehkharghani et al. [14] conducted sentiment analysis at document, sentence, and target levels, achieving the highest accuracy of 79.56% at the target level. Overall, findings in the literature suggest that while dictionary-based methods offer simplicity and domain independence, machine learning and deep learning approaches consistently outperform them in terms of accuracy and generalizability.

III. Method

Firstly, studies were initiated for the data collection process.

A. *Data Collection via the "Okul.com.tr" Platform*

Okul.com.tr is a website that provides information about both public and private schools at the preschool, primary, middle, and high school levels. Users can visit the platform to obtain information about schools and the facilities they offer. The website provides detailed information about each school. This includes images of the school, available facilities, user reviews, and contact information.To utilize the review data, the site administrators were contacted and permission was obtained. Within the scope of this permission, 1,000 anonymized user reviews related to primary schools located in Istanbul were collected. These reviews were then transferred to a database created specifically for this study in order to be processed and analyzed.

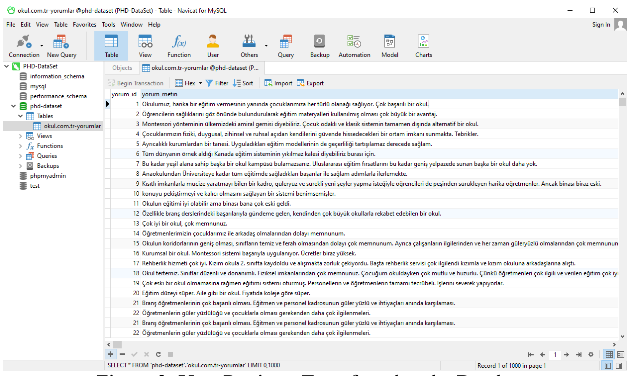


Figure 2: User Reviews Transferred to the Database

Figure 2 displays the appearance of the user reviews transferred from the Okul.com.tr website to the MySQL database.

B. *Data Labeling Process*

To identify the targets within the review texts and determine the sentiment associated with each target, assistance was obtained from three different education experts. Each expert independently identified the targets in the reviews and labeled their corresponding sentiments. Based on the feedback provided by all three experts, the final targets and sentiment labels for each review were determined.

C. *Preparation of Sentiment Lexicons for Use*

Within the scope of this study, the SentiWordNet and SentiTurkNet lexicons were utilized. SentiWordNet is an English-language lexicon containing 117,659 words [15]. On the other hand, SentiTurkNet is a lexicon prepared for the Turkish language, comprising 14,795 words [14].

D. *Preparation of ITU NLP Pipeline for Use*

For the utilization of the Turkish Natural Language Processing (NLP) Pipeline developed by Istanbul Technical University (ITU), a formal request was submitted to the responsible unit. Following the provision of authorized access credentials, the service was successfully integrated into the research workflow. Subsequently, a software interface was developed, and the pipeline was tested with its key components, including the Analyzer, Morphological Disambiguator, Named Entity Recognizer, and Syntactic Parser [16]. The reviews collected from the Okul.com.tr platform were processed through the ITU NLP Pipeline using the 'Whole Pipeline' class, which incorporates modules such as the Tokenizer, Normalizer, Morphological Tagger, Named Entity Recognizer, and Dependency Parser.

E. *Developed for Processing the Review Dataset with the ITU NLP Pipeline*

A software application was developed to process 1,000 reviews obtained from the Okul.com.tr website using the ITU NLP Pipeline. This software connects to the ITU NLP Pipeline, processes each review text, and transfers the results returned by the service into a MySQL database.

> *"Günümüzde bir ekol haline gelmeyi başarabilmiş en iyi özel okullar arasında sayılan bir kurum."*

Figure 4. Sample Review Text Sent for Processing to the ITU NLP Pipeline

Figure 4 shows a sample review text to be sent to the ITU NLP Pipeline for processing.

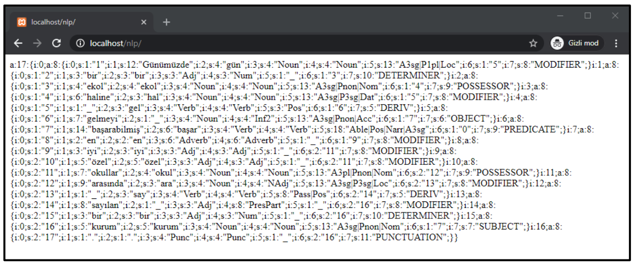


Figure 5. Sample Review Text Processed by the ITU NLP Pipeline

Figure 5 displays the output of a review text processed by the ITU NLP Pipeline. This procedure was applied to each review in the dataset, and the processed review texts were transferred to a MySQL database in a relational structure.

F. *Software Development for Related Word Detection*

In aspect-based sentiment analysis studies, identifying the words that describe the target is of critical importance. To determine the sentiment of a target, the sentiment of the words describing that target is examined. For detecting related words, the Dependency Parser included in the ITU NLP Pipeline was initially used. However, it was observed that the performance was insufficient, and therefore, a software tool was developed specifically for the detection of related words. The following considerations are taken into account when identifying related words:

- How many times does the target appear within the sentence?
- Is the target composed of a single word or multiple words?
- Is the word describing the target located within the same sentence as the target?

The script was executed on 1,000 reviews, and the related words were transferred to a MySQL database. Since related words were identified on a target basis, a new row was created in the database for each target occurrence within a sentence. As a result of the related word detection study for the targets, due to multiple targets within a single review text, 1,925 targets were identified across 1,000 reviews. Each target's associated review, the target's sentiment, and the related words were recorded in a relational format using the developed software.

Table 1. Sample Review Text Processed by the ITU NLP Pipeline

Sentiment	**Number of Targets**
Negative	452
Positive	1473
Total:	1925

G. Development of the Model for the Machine Learning Approach

Within the scope of this study, multilayer recurrent neural networks (RNNs), which are part of the machine learning approach, were utilized.

Step 1: The related words identified for each target are included as input to the model.

{bu okulun eğitim sistemi çok iyi}

Figure 6: Text Input Provided to the Model

Figure 6 presents the text data containing the related words provided as input to the model.

Step 2 (Tokenizer): Each word is converted into tokens, numerical values, using a tokenizer file created from the entire dataset.

[8, 21, 12, 7, 4, 2]

Figure 7: Numerical Representation of Each Word

Figure 7 illustrates the conversion of each word into numerical values using the tokenizer file.

Step 3 (Embedding): Word vectors are generated for the tokens.

[[0.67, 0.23, 0.42,....., 0.23],
[0.81, 0.21, 0.12,...., 0.21], ...]

Figure 8: Generated Word Vectors

Figure 8 displays the word vectors generated for the tokens. Word vectors are used to enhance the numerical representations of the words.

Step 4 (RNN): The multilayer recurrent neural network processes the incoming inputs.

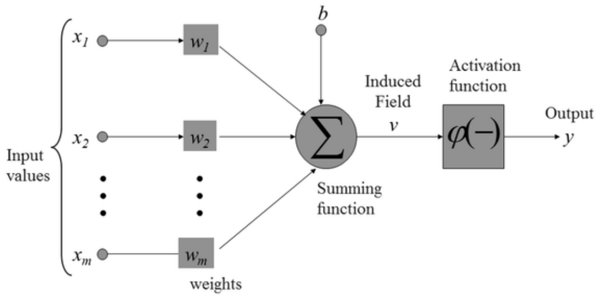


Figure 9: Operation of a Neuron [17]

Figure 9 illustrates the functioning of neurons, which are the fundamental building blocks of artificial neural networks.

$$u_k = \sum_{j=1}^{m} w_{kj} x_j$$

Figure 10: Neuron Operating Formula [18]

In neurons, which are the fundamental building blocks of artificial neural networks, each input x is multiplied by its corresponding weight w. The sum of these products is calculated and passed through an activation function. This value represents the output.

$$y_k = \varphi(u_k + b_k)$$

Figure 11: Activation Formula [18]

Figure 11 shows the formula for the activation function.

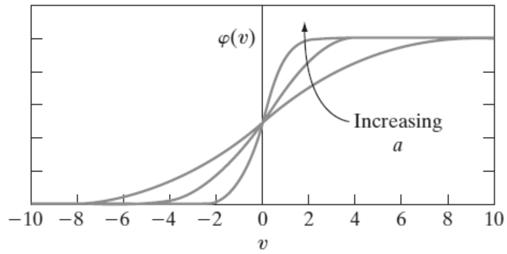


Figure 12: Graph of the Sigmoid Activation Function [18]

As shown in the graph in Figure 12, the sigmoid function is a nonlinear function that produces values between 0 and 1.

In the development of the model, the libraries numpy, pandas, json, and TensorFlow Keras were utilized. During the model creation process, the Sequential, Dense, GRU, Embedding, Adam, and Sklearn libraries, in addition to those mentioned above, were also utilized. The dataset was split into two parts for the purposes of training the model and subsequently testing it. Seventy percent (70%) of the dataset was used for training, while thirty percent (30%) was reserved for testing A three-layer recurrent neural network was used in the development of the model. The model consists of three main components:

- Embedding Layer (Word Vectors)
- GRU Layer (Multilayer Gated Recurrent Unit)
- Sigmoid Activation Function Layer

```
model = Sequential()
embedding_size = 20

model.add(Embedding(input_dim=2000,
                    output_dim=embedding_size,
                    input_length=20,
                    name='embedding_layer'))

model.add(GRU(units=12, return_sequences=True))
model.add(GRU(units=6, return_sequences=True))
model.add(GRU(units=3))
model.add(Dense(1, activation='sigmoid'))

optimizer = Adam(lr=1e-3)

model.compile(loss='binary_crossentropy',
              optimizer=optimizer,
              metrics=['accuracy'])

model.summary()
```

Figure 13: Code Snippet Creating the Embedding and RNN Structure

Figure 13 shows the code snippet that creates the Embedding and RNN structure. The RNN consists of three layers: the first layer has 16 neurons, the second layer has eight neurons, and the third layer has four neurons. The output from the RNN is processed by the sigmoid activation function, which compresses the value into the range between 0 and 1. If the value is close to zero, it is classified as negative; if close to one, it is classified as positive.

H. Model Development for the Lexicon-Based Approach

A three-step procedure was followed for the lexicon-based approach:

- Preparing the review dataset for processing,
- Developing the model,
- Testing with different lexicons and determining the performance rates.

The model was developed through a five-step process as follows:

- The review sentence is processed.
- Targets within the review sentence are identified.
- Word (dependency) chains related to the targets are constructed.
- The word chains corresponding to each target are sent to the lexicon for scoring.
- The sentiment of the target is determined.

$$P(a_i) = \frac{\sum_{k_j \in t_y} pos(k_j)}{|t_y|}$$

$$N(a_i) = \frac{\sum_{k_j \in t_y} neg(k_j)}{|t_y|}$$

$P(a_i) > N(a_i) \Rightarrow$ Positive
$P(a_i) < N(a_i) \Rightarrow$ Negative

Figure 14: Sentiment Decision Function [14]

Figure 14 presents the function responsible for determining sentiment. To calculate the positive score for each target:

- Each related word is sent to the lexicon.
- The positive scores obtained from the lexicon are summed.
- The total score is divided by the number of related words.
- The average positive score is calculated.

To calculate the negative score for a target:

- Each related word is sent to the lexicon.
- The negative scores obtained from the lexicon are summed.
- The total score is divided by the number of related words.
- The average negative score is calculated.

If the average positive score is higher than the average negative score, the sentiment of the target is considered positive. Conversely, if the average negative score is higher than the average positive score, the sentiment of the target is classified as negative.

IV. Result and Discussion

The developed model was tested with different numbers of layers, neurons, and training epochs. The highest accuracy rate and the lowest loss value were achieved with a three-layer architecture. Below are the results of the model with the three-layer structure.

Table 2. Accuracy Rates of the Model with Three-Layer Architecture

Neuron Configurations	**Epoch = 5**	**Epoch = 10**	**Epoch = 15**
8-4-2	loss: 0.1776 - acc: 0.9517	loss: 0.1649 - acc: 0.9586	loss: 0.1815 - acc: 0.9310
12-6-3	loss: 0.1631 - acc: 0.9517	loss: 0.1591 - acc: 0.9621	loss: 0.1613 - acc: 0.9619
16-8-4	loss: 0.1620 - acc: 0.9483	loss: 0.1585 - acc: 0.9552	loss: 0.1642 - acc: 0.9345
20-10-5	loss: 0.1534 - acc: 0.9483	loss: 0.1608 - acc: 0.9483	loss: 0.1609 - acc: 0.9448
24-12-6	loss: 0.1501 - acc: 0.9586	loss: 0.1709 - acc: 0.9517	loss: 0.1736 - acc: 0.9414

As shown in Table 2, the highest accuracy in the three-layer structure was observed with a neuron configuration of 3-6-12 and a training epoch value of 10. In this configuration, the loss value was 0.1591, and the accuracy was 0.9621.

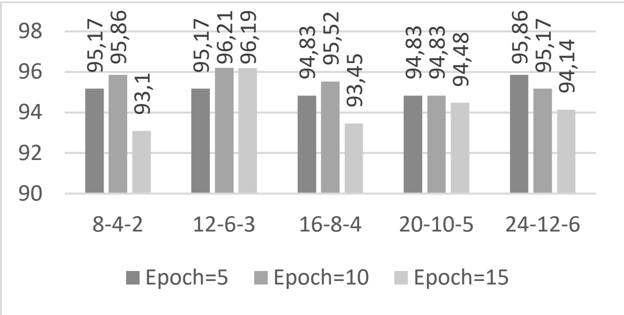


Figure 15: Accuracy Rates of the Model with Three-Layer Architecture

Figure 15 shows the graph of accuracy rates for the model with a three-layer architecture. As observed in the graph, the lowest accuracy achieved was 94.14%, while the highest accuracy reached 95.81% in the three-layer structure.

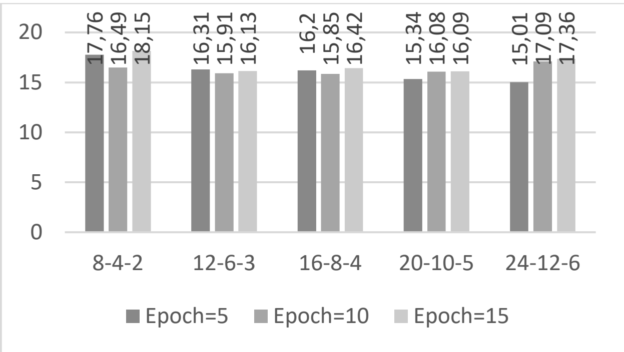
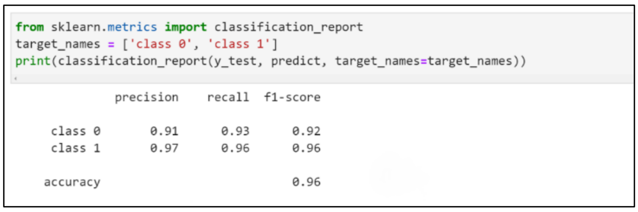


Figure 16: Loss Rates of the Model with Three-Layer Architecture

Figure 16 shows the graph of loss rates for the model with a three-layer architecture. As observed in the graph, the lowest loss rate achieved was 15.01%, while the highest loss rate reached 18.15% in the three-layer structure.



```
from sklearn.metrics import classification_report
target_names = ['class 0', 'class 1']
print(classification_report(y_test, predict, target_names=target_names))

              precision    recall  f1-score

     class 0       0.91      0.93      0.92
     class 1       0.97      0.96      0.96

    accuracy                           0.96
```

Figure 17: F-score Results Obtained Using the Sklearn Library

Figure 17 displays the F-score values obtained using the Sklearn library. Class 0 represents the negative polarity, while Class 1 represents the positive polarity. As shown in the figure, for the negative polarity, the precision value is 0.91, the recall value is 0.93, and the corresponding F-score is 0.92. For the positive polarity, the precision value is 0.97, the recall value is 0.96, and the corresponding F-score is 0.96. F-score values obtained using the Sklearn library. Class 0 represents the negative polarity, while Class 1 represents the positive polarity. As shown in the figure, for the negative polarity, the precision value is 0.91, the recall value is 0.93, and the corresponding F-score is 0.92. For the positive polarity, the precision value is 0.97, the recall value is 0.96, and the corresponding F-score is 0.96. For testing the model developed within the lexicon-based approach, the sentiment lexicons SentiTurkNet and SentiWordNet were used. The following accuracy formula was used to calculate the model's accuracy. The accuracy of the model is calculated by dividing the sum of true positives (TP) and true negatives (TN) by the total number of targets.

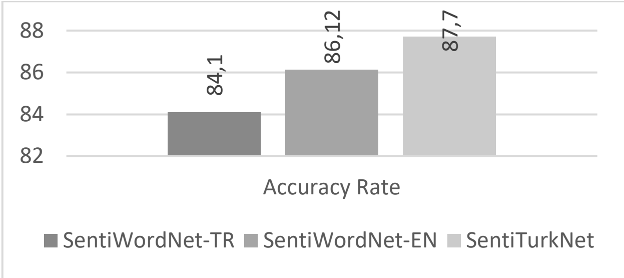


Figure 18: Accuracy Rates Obtained Using the Lexicon-Based Approach

Figure 18 presents the accuracy rates obtained using the lexicon-based approach. As shown in the graph, the highest accuracy was achieved with the SentiTurkNet lexicon, with an accuracy rate of 87.7%. The lowest accuracy rate was obtained using the lexicon derived from the Turkish translation of SentiWordNet, which was determined to be 84.1%. In the scenario where the English version of the SentiWordNet lexicon was used by translating the related words describing the targets into English for scoring, an accuracy rate of 86.12% was observed.

V. CONCLUSION

A. *Evaluation of the Results Obtained from the Machine Learning Approach*

Within the scope of the machine learning approach, multilayer recurrent neural networks (RNNs) were employed. Accordingly, architectures with 2, 3, 4, and 5 layers and various neuron configurations were constructed. Gated Recurrent Unit (GRU) was used in the development of these architectures. The highest accuracy rate was achieved with a three-layer architecture with a neuron configuration of 3-6-12 and a training epoch value of 10. The highest accuracy obtained was 96.12%. The lowest accuracy rate was observed in a five-layer architecture with a neuron configuration of 96-48-24-12-6 and a training epoch value of 15, yielding an accuracy of 92.07%. In the developed model, as the number of layers and epochs increased, the performance improved, but after a certain point, due to overfitting, the performance plateaued and began to decline. F-score values were also calculated for each sentiment class in the developed model. For the positive class, the precision was 0.97, recall was 0.96, and the resulting F-score was 0.96. For the negative class, the precision was 0.91, recall was 0.93, and the F-score was 0.92. These results indicate that the developed model is capable of accurately classifying each sentiment polarity (positive-negative) with a high degree of accuracy. F-score calculation is especially important in imbalanced and scattered datasets where the distribution is not uniform. In such datasets, accuracy alone may not be sufficient. The model's ability to correctly classify each class should be carefully evaluated.

Table 3: SWOT Analysis Table for the Machine Learning Approach

Strengths	**Weaknesses**
1. Higher accuracy rates compared to the lexicon-based approach. 2. Faster processing and higher performance. 3. Absence of problems commonly associated with traditional programming techniques.	1. Greater complexity of technical processes. 2. The requirement for labeled data. 3. The necessity of a training phase for the model. 4. The developed model operates within a single domain.
Opportunities	**Threats**
1. Opportunities provided by being a relatively new field in terms of model and approach development.	1. Dependence on external resources and developers due to the predominant use of ready-made libraries during model development

The machine learning approach, being a relatively new method compared to the lexicon-based approach, offers opportunities for developing new models and techniques. However, the frequent reliance on pre-built libraries during the model development process increases dependency on external resources and developers.

B. Evaluation of the Results Obtained from the Lexicon-Based Approach

Within the scope of the lexicon-based approach, three different sentiment lexicons were used: SentiWordNet-TR, SentiWordNet-EN, and SentiTurkNet. SentiWordNet-TR was obtained by translating the SentiWordNet lexicon into Turkish and contains 73,386 Turkish words. The model developed using this lexicon was tested, achieving an accuracy rate of 84.1%. SentiWordNet-EN is a sentiment lexicon developed using the WordNet lexicon and includes 117,659 English words. The model developed using this lexicon achieved an accuracy rate of 86.12%. SentiTurkNet is a sentiment lexicon developed in Turkish and contains 14,795 words. The model developed with this lexicon achieved an accuracy rate of 87.7%. As observed from the results, the highest accuracy was obtained with the SentiTurkNet lexicon. Although the number of words in this lexicon is lower than in the others, it yielded higher accuracy. The main reason for this is that the lexicon was developed specifically for the Turkish language. Despite having a larger word count, the SentiWordNet-TR lexicon experienced sentiment losses during the translation process into Turkish, resulting in an accuracy rate of 84.1%. The SentiWordNet-EN lexicon scenario involved using the original English lexicon without translation, where related words describing the target were translated into English and then scored. This scenario resulted in a 2% increase, achieving an accuracy rate of 86.12%.

Table 4: SWOT Analysis Table for the Dictionary Based Approach

Strengths	**Weaknesses**
1. The technical processes are relatively simple. 2. There is no need for a training phase for the model. 3. It is domain-independent.	1. Being limited by the capability and capacity of the dictionary. 2. Accuracy rates are lower compared to the machine learning approach. 3. The number and capacity of Turkish sentiment dictionaries are insufficient compared to those in other languages.
Opportunities	**Threats**
1. "The limited number of Turkish sentiment dictionaries indicates a need for further research and development in this field.	1. Due to the dynamic nature of language as a living entity, sentiment lexicons may lose their relevance and accuracy over time. 2. The disbanding of the teams responsible for developing the lexicons may prevent the release of updated versions.

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