Fırat Üniversitesi Deneysel ve Hesaplamalı Mühendislik Dergisi

FUJECE
Fırat University Journal of Experimental and Computational Engineering

Transformer Tabanlı Yöntemlerin Restoran Yorumlarının Analizi Üzerindeki Başarımı

Mucahit KARADUMAN[1], Muhammed Bedir BAYDEMIR[2], Muhammed YILDIRIM [3]*

[1]Yazılım Mühendisliği, Mühendislik ve Doğa Bilimleri Fakültesi, Malatya Turgut Özal Üniversitesi, Malatya, Türkiye.
[2]Arapgir Meslek Yüksek Okulu, Malatya Turgut Özal Üniversitesi, Malatya, Türkiye.
[3]Bilgisayar Mühendisliği, Mühendislik ve Doğa Bilimleri Fakültesi, Malatya Turgut Özal Üniversitesi, Malatya, Türkiye.
[1]mucahit.karaduman@ozal.edu.tr, [2]muhammed.baydemir@ozal.edu.tr, [3]muhammed.yildirim@ozal.edu.tr

Geliş Tarihi: 3.02.2025
Kabul Tarihi: 24.03.2025
Düzeltme Tarihi: 20.02.2025
doi: https://doi.org/10.62520/fujece.1632266
Araştırma Makalesi

Alıntı: M. Karaduman, M. B. Baydemir ve M. Yıldırım, “Transformer tabanlı yöntemlerin restoran yorumlarının analizi üzerindeki başarımı”, Fırat Üni. Deny. ve Hes. Müh. Derg., vol. 4, no 2, pp. 351-362, Haziran 2025.

Öz

Duygu analizi, metinlerdeki duygusal tonları belirleyerek, müşteri geri bildirimlerinden sosyal medya paylaşımlarına kadar geniş bir alanda önemli veriler sağlar. Bu çalışmada, restoran yorumları kullanılarak duygu analizi gerçekleştirilmiştir. Çalışmada, duygu analizi için transformatör tabanlı bir model kullanılmıştır. Bu modellerin temelinde yer alan dikkat mekanizması, metin içindeki kelimelerin bağlamsal ilişkilerini dinamik olarak öğrenerek dilin anlamını daha iyi yakalar. Model, geniş bir bilgi kaynağına sahip bir veri seti ile eğitilmiş ve test edilmiştir. Öncelikle veri setinin tokenleştirme ve dolgu işlemleri gerçekleştirilmiş; daha sonra model eğitilmiş ve test sonuçları elde edilmiştir. Modelin eğitim doğruluğu %90,81, test doğruluğu ise %85,79 olarak hesaplanmıştır. Diğer performans metrikleri de göz önünde bulundurulduğunda, negatif ve pozitif sınıflar için yüksek başarı elde eden model, nötr sınıf için daha düşük bir başarı göstermiştir. Genel değerlendirme açısından modelin doğruluk oranı göz önüne alındığında, iyi bir performans sergilediği görülmektedir. Bu durum, transformatör tabanlı yaklaşımların doğal dil işleme için uygun olduğunu ve bu alandaki kullanılabilirliğini göstermektedir.

Anahtar kelimeler: Duygu analizi, Transformatör, NLP, Metin sınıflandırma

*Yazışılan Yazar

İntihal Kontrol: Evet – Turnitin
Şikayet: fujece@firat.edu.tr

Firat University Journal of Experimental and Computational Engineering

FUJECE

Performance of Transformer-Based Methods on Restaurant Reviews Analysis

Mucahit KARADUMAN[1], Muhammed Bedir BAYDEMIR[2], Muhammed YILDIRIM[3*]

[1]Software Engineering, Faculty of Engineering and Natural Sciences, Malatya Turgut Ozal University, Malatya, Türkiye.
[2]Arapgir Vocational School, Malatya Turgut Ozal University, Malatya, Türkiye.
[3]Computer Engineering, Faculty of Engineering and Natural Sciences, Malatya Turgut Ozal University, Malatya, Türkiye.
[1]mucahit.karaduman@ozal.edu.tr, [2]muhammed.baydemir@ozal.edu.tr, [3]muhammed.yildirim@ozal.edu.tr

Received: 3.02.2025
Accepted: 24.03.2025

Revision: 20.02.2025

doi: https://doi.org/10.62520/fujece.1632266
Research Article

Citation: M. Karaduman, M. B. Baydemir and M. Yıldırım, "Performance of transformer-based methods on restaurant reviews analysis", Firat Univ. Jour.of Exper. and Comp. Eng., vol. 4, no 2, pp. 351-362, June 2025.

Abstract

Sentiment analysis provides important data in various areas, from customer feedback to social media posts, by determining the text's emotional tones. In this study, sentiment analysis was performed using restaurant reviews with a transformer-based model. The attention mechanism underlying these models dynamically learns the contextual relationships of words in the text and better captures the meaning of the language. The model was trained and tested using a dataset from a vast information source. First, tokenization and padding operations of the dataset were performed; then, the model was trained, and test results were obtained. The training accuracy of the model was calculated as 90.81% and the test accuracy as 85.79%. When other performance metrics were also considered, the model, which achieved high success for negative and positive classes, showed lower success for the neutral class. In terms of general evaluation, it is seen that the model exhibited good performance when the accuracy rate was taken into account. This shows that transformer-based approaches are suitable for natural language processing and usability in this area.

Keywords: Sentiment analysis, Transformer, NLP, Text classification

*Corresponding author

Plagiarism Checks: Yes – Turnitin
Complaints: fujece@firat.edu.tr

1. Introduction

In today's digitalized lifestyle, comments on online platforms are effective in decision-making processes in many areas, and consumers decide whether to take action based on these comments. In particular, elements in the natural flow of life, such as shopping, holiday planning, and reservations, have found their place on digital platforms. Digital platforms provide convenience in decision-making by saving time and providing a wide range of opportunities to analyze user comments. These services, which are an indispensable part of modern life, offer healthy progress to improve process efficiency and reliability by providing solutions and suggestions to users, especially regarding user experiences. Transactions that can be performed on the Internet are listed in general in Figure 1. These processes include determining the emotional tone of texts with sentiment analysis, categorizing content with text classification, and automatic translation between different languages with language translation. In addition, long content can be shortened with text summarization algorithms, and user interactions can be automated with chatbots and virtual assistants. Search and information extraction processes enable meaningful information to be extracted from large data sets, while speech recognition technologies convert voice input into text. Automatic text completion and language modeling techniques speed up the writing process and improve the user experience. News and spam filtering prevent unnecessary content, providing a safe internet environment, while recommendation systems help provide personalized content presentation. Finally, social media analysis provides data-driven insights into user tendencies, trends, and social events.

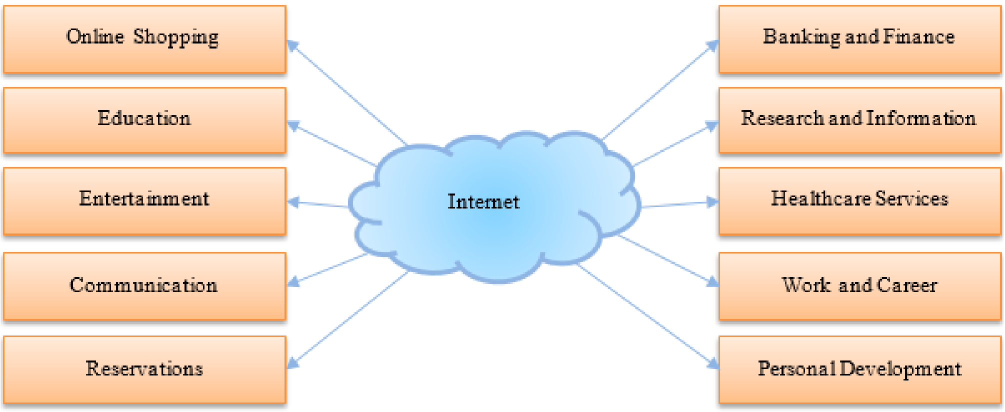

Figure 1. General list of transactions that can be done via the Internet

The Internet can be used for reservations, vacations, and restaurant dining. Customer experiences in the restaurant and service sector help companies to see their shortcomings and improve them, as well as to have prior knowledge about what kind of service they will receive. Restaurant reviews, also the subject of this study, are presented as a source of information regarding food quality, service, and general satisfaction. These reviews, which are on different platforms and are irregular, can make it difficult for users and company owners to access and analyze the correct information. These difficulties can cause mistakes when making the right decision. The development of artificial intelligence models, especially in natural language processing (NLP), offers significant benefits in interpreting and analyzing texts. Classifying complex texts by analyzing them and extracting meaningful information are among the essential tasks of NLP systems. Thanks to these systems, studies such as sentiment and subject-based analysis can be carried out from texts. Measuring the satisfaction levels of restaurant reviews, detecting sentiments in the text, and determining trends and changes are essential in improving service quality and providing correct analysis opportunities to customers and business owners. The operations performed with natural language processing are shown in Figure 2 [1–8]. Remarkably, the classification of texts is within the scope of this study.

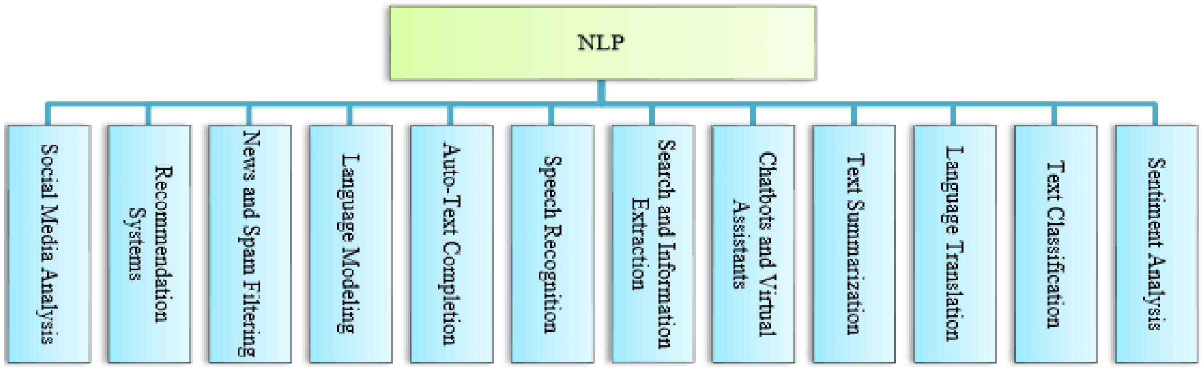

Figure 2. Applications made with NLP

This article is about analyzing restaurant reviews. When the studies in the literature are examined, there are many studies in the field of NLP. NLP offers a wide range of applications in the processing, analyzing, and interpreting text and speech data. Studies in this field focus on basic tasks such as Sentiment Analysis [9], Text Classification [10], Language Translation [11], and Text Summarization [12]. In addition, significant progress has been made in areas such as Chatbots and Virtual Assistants [13], Search and Information Extraction [14], Speech Recognition [15], Auto-Text Completion [16] and Language Modeling [17]. Applications such as News and Spam Filtering [18,19] Recommendation Systems [20], and Question-Answering task [21] increase the impact of natural language processing technologies in daily life and offer a wide range of usage scenarios. Studies in these areas enable NLP to provide more effective and efficient solutions in various sectors.

The literature contains studies on the subject. Luo et al. compared deep learning-based models to analyze restaurant reviews. The study stated that the most successful results were obtained from LSTM networks when sentiment analysis from restaurant reviews was performed. In this study also inferred that the most negative comments were in April, during the epidemic. In the study, researchers achieved an accuracy of 91.1% [22]. In this study, Asani et al. made different inferences to perform sentiment analysis on restaurant reviews. After sentiment analysis, they developed a recommendation system that considered user comments. The study evaluated restaurants using different performance measurement metrics. It obtained a precision value of 92.8% [23]. Punetha et al. present an unsupervised mathematical optimization framework for sentiment analysis in restaurant reviews. They developed this method because many studies in the literature have a complex and lengthy training process. The study was tested on two different data sets. Precision values of 89% and 90% were obtained in these datasets [24]. Patil et al. used deep and machine learning methods to classify restaurant reviews. This study concluded that Naive Bayes and Logistic regression models were more successful than other machine learning methods. The parameters of these two models were optimized with the grid search algorithm. The accuracy values obtained in this step were 89.6% and 89.9%, respectively. CNNs, which are deep learning architectures, achieved an accuracy value of 89%, and Bi-LSTM networks, 90% [25]. Khan et al. stated that traditional methods could not produce successful results in such studies and proposed a new model. A bidirectional LSTM network was proposed in the proposed model. The proposed model was tested on three different data sets. As a result of the evaluations, the proposed model reached 78.96%, 79.10%, and 79.03% F1-Score in three data sets, respectively [26]. Mamatha et al. followed a different method in their study. This study used images instead of text to analyze restaurant reviews. They stated that the metrics obtained from image classification were more successful than those obtained by Naive Bayes. Researchers used CNN networks in the image classification process [27]. Zahoor et al. focused on analyzing restaurant reviews in a specific region in their study. In the study, researchers made a two-way inference. The first was emotion detection, while the second was related to automatic feedback. The study compared the results obtained using different machine learning methods. It was stated that the best results were achieved in the Random Forest method [28]. Branco et al. used transfer learning and transformer methods in their study to analyze restaurant reviews. Recently, transformer-based methods have been frequently preferred, especially in natural language processing. In this proposed model, they achieved an accuracy value of 84% in a 3-class emotion analysis detection [29].

This article analyzes restaurant reviews using natural language processing methods and classifies the reviews using the transformer-based method. The aim is to classify the reviews correctly, divide them into three groups, and understand the restaurant reviews, which are very complex and challenging to analyze and determine trends. This study gives information about the proposed model's general structure and the dataset used in section 2. In section 3, experimental results and performance metrics of the model applied to the dataset are included. The last section includes evaluation, interpretation, and recommendations for the results obtained.

2. System Theory

2.1. Dataset

The restaurant reviews dataset is a good source for analyzing restaurants, consisting of customer feedback [30]. The dataset, which consists of approximately 513,000 rows in general, consists of a two-column structure. While customer reviews are given with the title “text” in the dataset, the column that determines the emotional states is called “label.” Customer reviews are collected in three classes. These classes are numbered negative, neutral, and positive. The comments, which consist of a large amount of text in the dataset, provide a good source for NLP models.

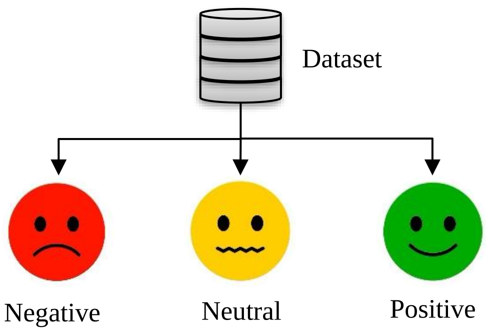

Figure 3. Dataset visualization by face icon

The simulation representation of the dataset is given in Figure 3. In Figure 3, negative, neutral, and positive classes are shown with facial expressions. A sad face expression was selected for negative, an expressionless face was selected for neutral and a smiling face was selected for positive.

2.2. Transformer based model

Transformer-based models are becoming popular due to successful image processing and text analysis results. It is seen that using the Transformer architecture provides high success results with NLP from complex texts. In the Deep Learning architecture used in this study, the Transformer block is used, and thus, the model is aimed to have high classification success. The general structure of the proposed system is given in Figure 4. First, data is taken from the ready restaurant review dataset, and tokenization and padding operations are performed during the pre-processing step.

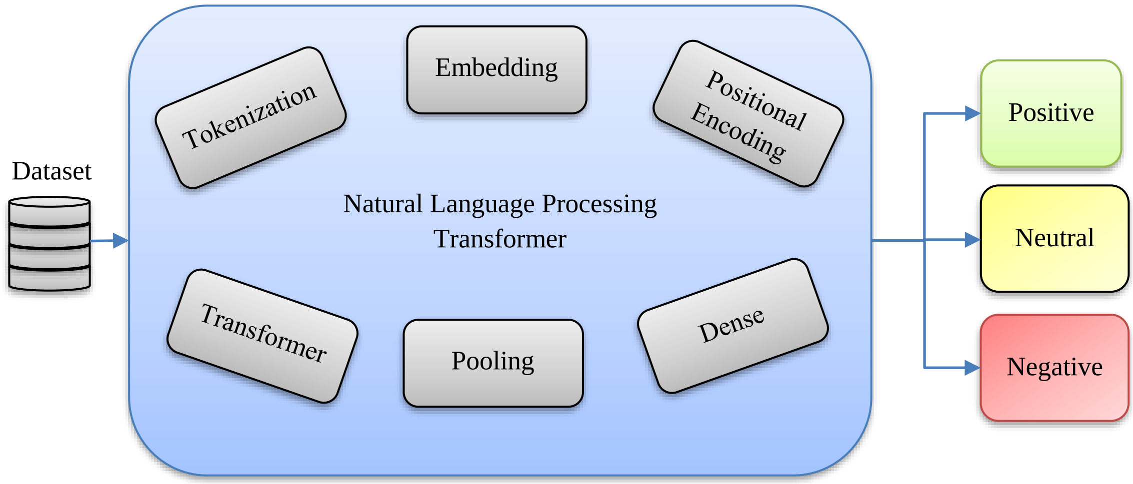

Figure 4. General structure of the Transformer method

The tokenization process is given in Figure 5. Sentences are analyzed one by one, and tokens are created. The tokenization process separates texts into subunits, such as words, and allows them to be represented with numerical indexes. For this purpose, the tokenizer class of the Keras library is used to convert the most used 20 thousand words into a word dictionary. The texts in the created word dictionary are converted into numerical sequences and converted into a usable format in the model.

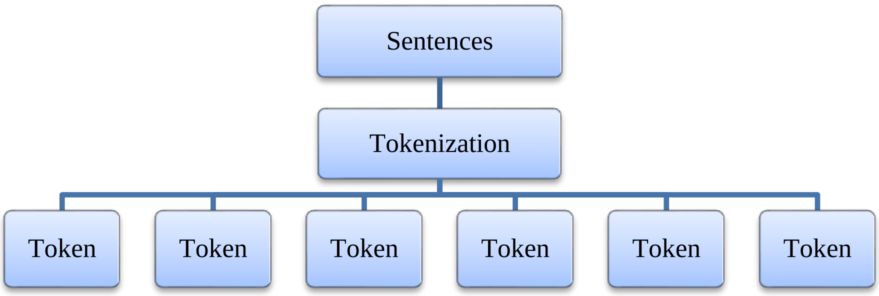

Figure 5. Tokenization processes

After the tokenization process, the padding step is started. In this step, the lengths of the sequences obtained after the tokenization process are equalized. The maximum length is determined as 200, and all sequences' length is adjusted according to this value. Zero values are added to the short sequences at this stage, and the long sequences are limited to 200 tokens. This standardization allows the data to be input into the model with a fixed length. At this stage, the training and testing processes of the model will begin.

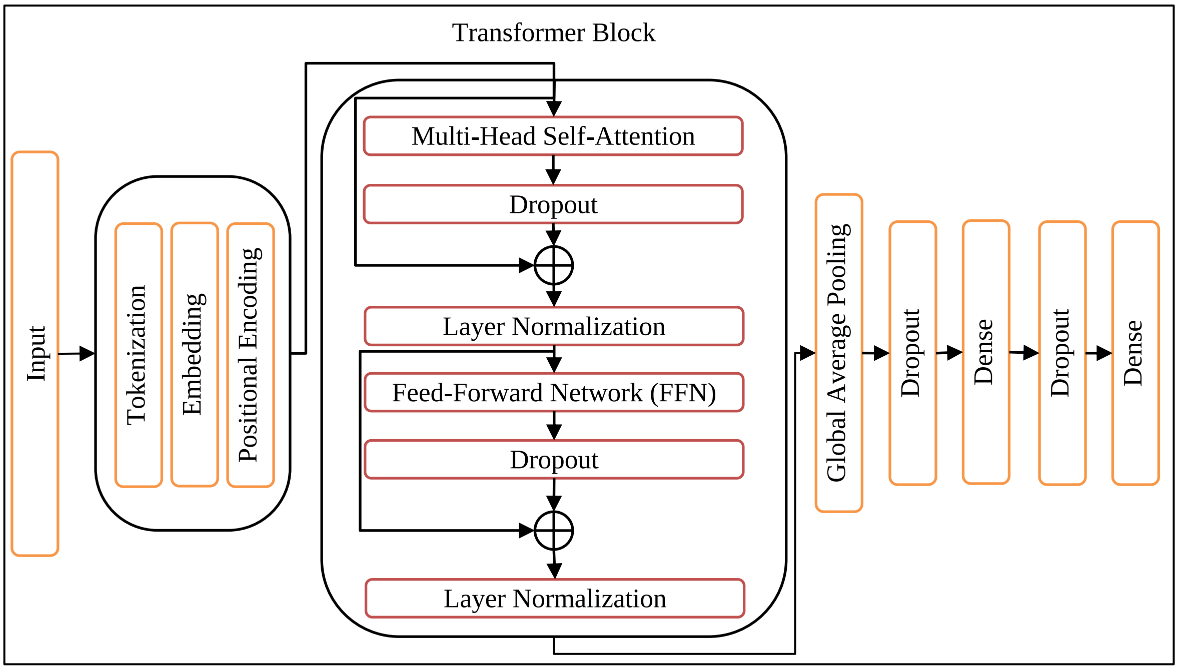

Figure 6. Transformer-based model structure

The structure of the transformer-based model is given in Figure 6 [31]. The model structure starts at the input layer and consists of token and position embedding layers, transformer block, global average pooling, dropout, dense, dropout, and dense layers. The model, which takes 200 parameters as input, is designed to have three classes at the output. The model's embedding size is 32, and the number of attention heads to focus on is determined as 2. The dropout value is entered as 0.2. 70% of the data used for the model is used for training and 30% for testing. The learning rate of the model is determined as 0.0001, and the batch size is entered as 32. The model was run for 20 epochs, and 11243 operations were performed in each epoch. Performance metrics were obtained with the values obtained by running the model, and comments were made about the model. Accuracy, F1 score, recall, and precision values were calculated as performance metrics [32]. The calculation formulas of these metrics are given in Table 1.

Table 1. Performance metrics

Performance Metric	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1-Score	$2 \cdot \frac{(Precission \cdot Recall)}{(Precission + Recall)}$

The accuracy rate measures the correct prediction rate of the model. Precision expresses the ratio of true positive predictions to all positive predictions. Recall value determines the correct classification rate of true positive examples. The F1 score also provides a measure of the balance of precision and recall values. The overall performance of the model is determined with these calculated metrics.

3. Experimental Result

The restaurant reviews dataset [30] is a text dataset consisting of approximately 513,000 rows and containing the classes negative, neutral), and positive, as shown in the graph in Figure 7.

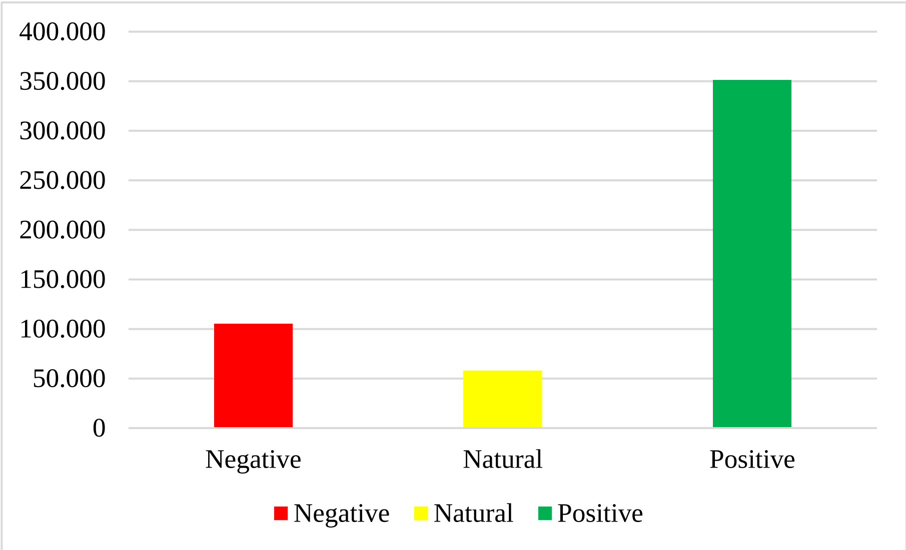

Figure 7. Restored comment dataset class data numbers

The tokenization step was carried out by considering the 20,000 most used words and tokens that were created. The maximum length of the tokens created was set to 200, and zeros were added to the short ones, while the long ones were limited to 200.

This prepared data was given as input to the model. The AdamW algorithm was used as an optimizer in the model and the learning rate was set to 0.0001. The batch size was set to 32 and the model was run for 20 epochs. The data was set as 70% training and 30% testing as input to the model, and the evaluation was made in this way. The graph showing the change in training and test accuracy according to epochs is given in Figure 8. When the graph is examined, it is observed that the accuracy of the model increases steadily in each epoch during the training period. The fact that the model's learning success in the training data reaches a high value of 90.81% shows that it has a strong ability in terms of generalization.

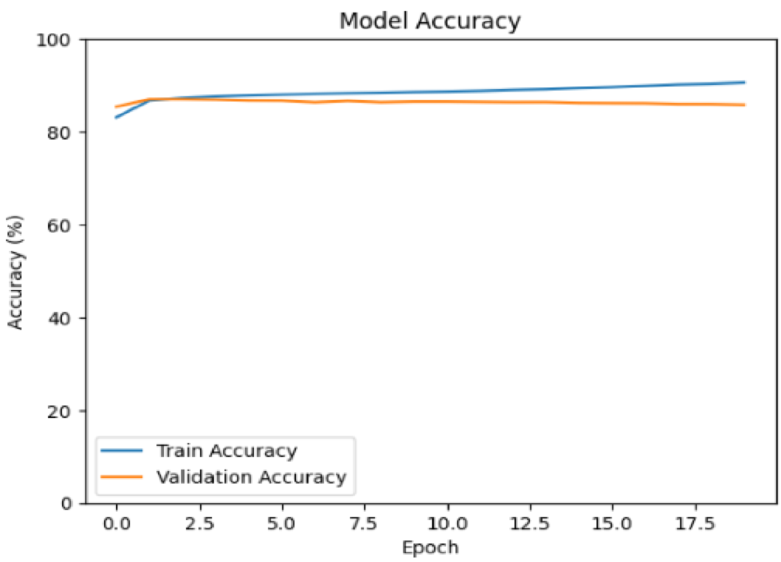

Figure 8. Model accuracy graph for train and test

The test accuracy rate was calculated as 85.79%. The difference in accuracy rate between test and training data shows that the model has a limited margin of error. This result shows that the model does not overfit and generalizes well for the data used for validation. Balancing the model's accuracy rates for training and test data shows that patterns are learned for both data sections, and a stable performance is achieved.

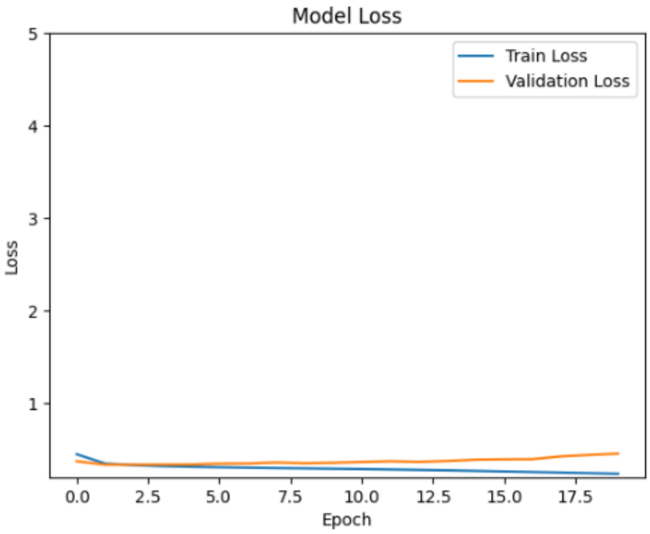

Figure 9. Model loss graphic for train and test

The graph showing the loss value of the model is given in Figure 9. During the training process, the loss value of the model decreases continuously and stabilizes after a certain point. The loss value on the training data was calculated as 0.2307. This value indicates that the training errors are minimized and the patterns are mostly recognized correctly. It indicates that the model is successfully optimized, and the relationship between the input and output is correctly established. The loss value calculated on the test data was determined as 0.4543. The difference between the training and test shows that the model has a certain margin of error. The low error margin indicates that the model generalizes on the test data and that there is no over-learning. The fact that the training and test losses are low and close to each other shows that the model exhibits a balanced performance. The confusion matrix created with the test data in line with the obtained results is given in Figure 10.

True Label \ Predicted Label	Negative	Neutral	Positive
Negative	26649	2446	2441
Neutral	4934	4734	7589
Positive	2147	2358	100885

Figure 10. Confusion matrix

Calculations were also made for other performance metrics; the results are shown in Table 2. The model performance seems to be successful for the class with negative comments. Precision 79%, Recall 85% and F1 Score 82% were calculated. It is seen that the generalization ability of the model for this class is good, and it has successful results. The performance values of the class with neutral comments were determined as a Precision of 50%, Recall of 27%, and F1 Score of 35%. These values remained low, and it is understood that the generalization and accuracy of the prediction for this class are insufficient. This problem is caused by the data set being unbalanced. It is seen that the performance of the class with positive comments is good, and Precision 91%, Recall 96%, and F1 Score 93% were calculated. These results show that the model's generalization ability and correct prediction rate for this class are high, and it has achieved successful results.

Table 2. Model performance metrics results (%)

Class	Precision	Recall	F1 Score
Negative	79.00	85.00	82.00
Natural	50.00	27.00	35.00
Positive	91.00	96.00	93.00
General Performance	83.89	85.79	84.42

As seen in Table 2, a precision value of 83.89% was obtained in this study to analyze restaurant reviews. Eliminating the imbalance in the dataset or increasing the number of comments will increase the model's performance.

4. Conclusion

In the study, a transform-based model was used to classify restaurant reviews using the NLP method. The model was trained with a comprehensive dataset of 3 classes, and tests were performed. The model's performance was evaluated using accuracy, precision, recall, and F1 score metrics. The test accuracy of the model was calculated as 85.79%. When the general results are examined, it is seen that the model achieves high performance in negative and positive classes. At the same time, it achieves limited success for the neutral class. The rates in the neutral class may be due to the uncertainty in the class or the imbalance in the dataset. In line with the calculated performance results, it is interpreted that the model is a successful approach for sentiment classification from restaurant reviews. This study shows that the transformer architecture provides effective results in NLP problems and contributes to the field of text classification. The imbalance of the dataset is the study's limitations. Testing the proposed model with a more comprehensive dataset is important to produce more realistic results.

5. Author Contribution Statement

Authors 1, author 2, and author 3 prepared the study concept and design, performed the experiments, and analyzed and interpreted the data. Author contributions are equal.

6. Ethics Committee Approval and Conflict of Interest

There is no need for an ethics committee approval in the prepared article. There is no conflict of interest with any person/institution in the prepared article.

7. Ethical Statement Regarding the Use of Artificial Intelligence

No artificial intelligence-based tools or applications were used in the preparation of this study. The entire content of the study was produced by the author in accordance with scientific research methods and academic ethical principles

8. References

[1] S. K. Mohapatra, P. K. Sarangi, P. K. Sarangi, P. Sahu, and B. K. Sahoo, "Text classification using NLP based machine learning approach," in *AIP Conf. Proc.*, 2022.
[2] H. Liu, Q. Yin, and W. Y. Wang, "Towards explainable NLP: A generative explanation framework for text classification," *ArXiv Prepr. arXiv:1811.00196*, 2018.
[3] V. Dogra *et al.*, "A Complete Process of Text Classification System Using State-of-the-Art NLP Models," *Comput. Intell. Neurosci.*, Art. no. 1883698, 2022.
[4] Q. Zhao *et al.*, "Leveraging sensory knowledge into Text-to-Text Transfer Transformer for enhanced emotion analysis," *Inf. Process. Manag.*, vol. 62, Art. no. 103876, 2025.
[5] M. Razno, "Machine learning text classification model with NLP approach," *Comput. Linguist. Intell. Syst.*, vol. 2, pp. 71–73, 2019.
[6] Z. Li *et al.*, "A unified understanding of deep NLP models for text classification," *IEEE Trans. Vis. Comput. Graph.*, vol. 28, pp. 4980–4994, 2022.
[7] J. Barbosa *et al.*, "Evaluating the noise tolerance of Cloud NLP services across Amazon, Microsoft, and Google," *Comput. Ind.*, vol. 164, Art. no. 104211, 2025.
[8] S. Feuerriegel *et al.*, "Using natural language processing to analyse text data in behavioural science," *Nat. Rev. Psychol.*, pp. 1–16, 2025.
[9] M. Arzu and M. Aydogan, "Türkçe Duygu Sınıflandırma İçin Transformers Tabanlı Mimarilerin Karşılaştırılmalı Analizi," *Comput. Sci.*, pp. 1–6, 2023.
[10] P. Guleria, "NLP-based clinical text classification and sentiment analyses of complex medical transcripts using transformer model and machine learning classifiers," *Neural Comput. Appl.*, pp. 1–26, 2024.
[11] S. H. Ahammad *et al.*, "Improved neural machine translation using Natural Language Processing (NLP)," *Multimed. Tools Appl.*, vol. 83, pp. 39335–39348, 2024.
[12] D. Van Veen *et al.*, "Adapted large language models can outperform medical experts in clinical text summarization," *Nat. Med.*, vol. 30, pp. 1134–1142, 2024.
[13] A. Selvi *et al.*, "COLLEGEBOT: Virtual Assistant System for Enquiry Using Natural Language Processing," in *2nd Int. Conf. Intell. Data Commun. Technol. Internet Things*, pp. 1407–1414, 2024.
[14] Z. Wang, "Information Extraction and Knowledge Map Construction based on Natural Language Processing," *Front. Comput. Intell. Syst.*, vol. 7, pp. 47–49, 2024.
[15] M. Abdalla *et al.*, "An NLP-based system for modulating virtual experiences using speech instructions," *Expert Syst. Appl.*, vol. 249, Art. no. 123484, 2024.
[16] D. Chen *et al.*, "Complex visual question answering based on uniform form and content," *Appl. Intell.*, vol. 54, pp. 4602–4620, 2024.
[17] R. Patil *et al.*, "Next Word Prediction System Using NLP," in *IEEE Int. Conf. Smart Power Control Renew. Energy*, pp. 1–6, 2024.
[18] M. Yildirim, "Using and Comparing Machine Learning Techniques for Automatic Detection of Spam Website URLs," *NATURENGS*, vol. 3, pp. 33–41, 2022.
[19] M. Asmitha and C. R. Kavitha, "Exploration of Automatic Spam/Ham Message Classifier Using NLP," in *IEEE 9th Int. Conf. Converg. Technol.*, pp. 1–7, 2024.
[20] A. Mishra, S. K. Bisoy, and B. Naik, "Medication Recommendation System for Skin Diseases using NLP," in *Int. Conf. Adv. Smart, Secur. Intell. Comput.*, pp. 1–7, 2024.
[21] M. Arzu and M. Aydogan, "Comparison of Transformer-Based Turkish Models for Question-Answering Task," *Balk. J. Electr. Comput. Eng.*, vol. 12, pp. 387–393, 2025.
[22] Y. Luo and X. Xu, "Comparative study of deep learning models for analyzing online restaurant reviews in the era of the COVID-19 pandemic," *Int. J. Hosp. Manag.*, vol. 94, Art. no. 102849, 2021.
[23] E. Asani, H. Vahdat-Nejad, and J. Sadri, "Restaurant recommender system based on sentiment analysis," *Mach. Learn. Appl.*, vol. 6, Art. no. 100114, 2021.
[24] N. Punetha and G. Jain, "Game theory and MCDM-based unsupervised sentiment analysis of restaurant reviews," *Appl. Intell.*, vol. 53, pp. 20152–20173, 2023.
[25] R. N. Patil *et al.*, "Improving Sentiment Classification on Restaurant Reviews Using Deep Learning Models," *Procedia Comput. Sci.*, vol. 235, pp. 3246–3256, 2024.

[26] M. U. Khan *et al.*, "A novel category detection of social media reviews in the restaurant industry," *Multimed. Syst.*, vol. 29, pp. 1825–1838, 2023.
[27] M. Mamatha *et al.*, "Visual sentiment classification of restaurant review images using deep convolutional neural networks," in *IEEE Int. Conf. Electron. Comput. Commun. Technol.*, pp. 1–6, 2022.
[28] K. Zahoor, N. Z. Bawany, and S. Hamid, "Sentiment analysis and classification of restaurant reviews using machine learning," in *21st Int. Arab Conf. Inf. Technol.*, pp. 1–6, 2020.
[29] A. Branco *et al.*, "Sentiment analysis in portuguese restaurant reviews: Application of transformer models in edge computing," *Electronics*, vol. 13, Art. no. 589, 2024.
[30] A. Nasef, "Restaurant Reviews," [Online]. Available: https://www.kaggle.com/datasets/ahmedwaelnasef/restaurant-reviews. [Accessed: Jan. 10, 2025].
[31] A. Nandan, "Text classification with Transformer," [Online]. Available: https://keras.io/examples/nlp/text_classification_with_transformer. [Accessed: Jan. 23, 2025].
[32] M. Yildirim and A. Cinar, "Classification with respect to colon adenocarcinoma and colon benign tissue of colon histopathological images with a new CNN model: MA_ColonNET," *Int. J. Imaging Syst. Technol.*, vol. 32, pp. 155–162, 2022.