RoBERTa-Based Sentiment Analysis for Predicting Hotel Review Scores

Bardia Dehbasti
Dept. of Electrical and Computer Engineering
Toronto Metropolitan University
Toronto, Canada
bardia.dehbasti@torontomu.ca

***Abstract*—This project explores the application of transformer models, specifically the RoBERTa model for sentiment analysis to predict review scores for hotel reviews. By leveraging transformer-based models, the study aims to enhance the accuracy of sentiment classification for multi-class prediction (5-star, 4-star, 3-star, 2-star, and 1-star ratings). For this project, the hotel review data is preprocessed to remove noise and standardize the text. RoBERTa will be fine-tuned on this dataset to capture the nuanced sentiments expressed in the reviews with the aim to perform multi-class classification. Additionally, RoBERTa's performance will be compared with traditional sentiment analysis models, including the NLTK sentiment analyzer and the VADER model. Experimental results will demonstrate whether RoBERTa will significantly outperform both NLTK and VADER in terms of accuracy, precision, and F1-score. The goal is to assess the effectiveness of transformer-based models in a multi-class classification task and to compare their performance against older models.**

***Index Terms*—sentiment analysis, RoBERTa, hotel reviews, transformer models, NLP, NLTK, VADER**

I. Introduction

Many applications in natural language processing (NLP) require the ability to accurately classify sentiments expressed in text. Sentiment analysis techniques are commonly used to determine whether a piece of text conveys a positive, negative, or neutral sentiment. However, for certain applications, it is important to classify text into more granular categories. This project focuses on predicting review scores for hotel reviews, classifying them into five categories: 5-star, 4-star, 3-star, 2-star, and 1-star ratings.

Sentiment analysis, also known as opinion mining, is a computational study of people's opinions, sentiments, emotions, and attitudes expressed in written language. It involves various tasks such as identifying the polarity of the text (positive, negative, neutral), extracting subjective information, and determining the strength or intensity of the sentiment [11]–[14]. This field of study is crucial for understanding public opinion, improving customer service, and enhancing decision-making processes.

Traditional sentiment analysis techniques, such as those based on lexicons or basic machine learning models, often fall short in capturing the complex and nuanced sentiments present in customer reviews. Models like the NLTK sentiment analyzer [15] and VADER (Valence Aware Dictionary and sEntiment Reasoner) [16] have been widely used for sentiment classification tasks. However, these models may struggle with context-dependent sentiments and idiomatic expressions commonly found in hotel reviews. Additionally, they are often limited to binary or ternary classification, which is insufficient for applications requiring finer-grained sentiment distinctions.

In recent years, transformer-based models have revolutionized the field of NLP by achieving state-of-the-art performance across various tasks. Among these, BERT (Bidirectional Encoder Representations from Transformers) [17] and its extension RoBERTa (Robustly optimized BERT approach) [18] have shown remarkable capabilities in understanding context and capturing semantic nuances. These models are pre-trained on a large corpus and fine-tuned for specific tasks, making them highly effective for sentiment analysis. Their architecture allows for better handling of context-dependent sentiments and complex language patterns, making them suitable for multi-class classification tasks.

This project aims to leverage the advanced capabilities of RoBERTa for predicting review scores from hotel reviews. The study involves preprocessing a large dataset of hotel reviews to remove noise and standardize the text. RoBERTa is then fine-tuned on this dataset to accurately classify sentiments and predict review scores. Additionally, the performance of RoBERTa is compared with traditional sentiment analysis models, including the NLTK sentiment analyzer and the VADER model.

The rest of the project report is organized as follows: Section II is a literature review on related work on sentiment analysis techniques using BERT-based transformers. Section III describes the dataset and the preprocessing steps required to make a suitable input for the transformer model. Section IV details the problem statement. Finally, Section V describes the RoBERTa model and its architecture.

II. Literature Review

In a study by Ferdoshi et al. from the Hindustan Institute of Technology & Science, the effectiveness of VADER and RoBERTa models for sentiment analysis of learner reviews in Massive Open Online Courses (MOOCs) is explored. The research focuses on analyzing student sentiments from Coursera course reviews to enhance the overall educational experience. Two approaches were employed: lexicon-based analysis using VADER and transformer-based analysis using RoBERTa. The methodology involves collecting a dataset of 1.45 million course reviews from Coursera, followed by preprocessing and cleaning the data. Sentiment analysis was then performed using VADER, which classifies sentiments as positive, negative, or neutral, and RoBERTa, which uses a more nuanced sentiment classification approach. The analysis reveals sentiment patterns across different domains of study, specifically technical and medical courses. Experimental results indicate that RoBERTa outperforms VADER in terms of accuracy, precision, and F1-score, demonstrating the superiority of transformer-based models for sentiment analysis. However, VADER's lexicon-based approach provides finer sentiment classifications, capturing more nuanced sentiments within the reviews. The study also includes a temporal analysis of course reviews from 2019 and 2020, showing how learner sentiments evolved over time. This research highlights the importance of using advanced sentiment analysis models like RoBERTa to understand learner feedback in MOOCs. The findings emphasize the potential of sentiment analysis in improving educational experiences and identifying areas for course enhancement [10].

A recent study by Rahmania et al. analyzes customer sentiment for the Amazon Go store using VADER and RoBERTa models. The goal is to evaluate the effectiveness of these models in assessing customer reviews and star ratings sourced from Google Maps. Data collection and pre-processing were conducted on reviews from four Amazon Go locations in Seattle, and the experiments compared VADER and RoBERTa based on precision, recall, F1-Score, and accuracy. Their methodology incorporates VADER for lexicon-based sentiment analysis and RoBERTa for transformer-based sentiment analysis. The data preparation process involved cleaning, tokenization, and lemmatization of 967 reviews, which were then reduced to 623 after removing null entries. Sentiments were categorized based on review ratings: positive for ratings above 3, negative for below 3, and neutral for ratings of 3. The results indicate that RoBERTa surpasses VADER in overall accuracy and F1-score for positive sentiment classifications. In contrast, VADER demonstrated higher recall for positive sentiments. Additionally, the study revealed a significant correlation between the sentiment score and the star rating provided by customers. Visualization tools like word clouds and confusion matrices were utilized to assess model performance, showing that RoBERTa offers more reliable sentiment classification. This research underscores the potential of advanced NLP models like RoBERTa in sentiment analysis for smart retail. It emphasizes the importance of precise sentiment classification in enhancing customer experience and improving service quality in retail environments [9].

In another study, Kumar et al. from Presidency College, Bengaluru, investigate the effectiveness of VADER and RoBERTa for sentiment analysis of product reviews. This research explores the application of lexicon-based and transformer-based approaches to assess customer opinions on various products. The dataset comprises reviews from different product categories, providing a comprehensive analysis of customer sentiments. Their methodology incorporates VADER for lexicon-based sentiment analysis and RoBERTa for transformer-based sentiment classification. The dataset includes reviews from Amazon, which were preprocessed using the NLTK library for cleaning, tokenization, and stopword removal. VADER was used to assign sentiment scores based on valence, while RoBERTa was fine-tuned on the labeled dataset to capture nuanced sentiment expressions. Results indicate that RoBERTa outperforms VADER in overall accuracy, achieving an accuracy of 91%. VADER, however, provided useful insights into sentiment intensity and valence. This dual approach allows for a more robust assessment of sentiment in product reviews, combining the strengths of both models. The study emphasizes the importance of integrating advanced NLP models for sentiment analysis in e-commerce, highlighting the potential benefits for businesses in understanding customer feedback and improving product offerings. This comprehensive approach demonstrates the value of combining lexicon-based and transformer-based methods to achieve high accuracy and detailed sentiment analysis [8].

Archa Joshy and Sumod Sundar from the TKM College of Engineering, Kollam, Kerala, conducted a study to compare the performance of BERT, DistilBERT, and RoBERTa models for sentiment analysis. This research aims to evaluate the efficacy of these transformer-based models on movie reviews and tweets datasets, specifically the Sentiment140 and Coronavirus tweets NLP datasets. The methodology includes preprocessing the datasets, which involves cleaning, tokenization, and handling class imbalance. The models are then fine-tuned on the prepared datasets. BERT, DistilBERT, and RoBERTa are compared in terms of their training accuracy, validation accuracy, and testing accuracy. The results indicate that BERT outperforms the other two models in both datasets, achieving a training accuracy of 95.3%, validation accuracy of 93.13%, and testing accuracy of 92.76% on the Sentiment140 dataset. On the Coronavirus tweets NLP dataset, BERT achieved a training accuracy of 94.1%, validation accuracy of 81.3%, and testing accuracy of 90.43%. The study also details the environmental setup used for the experiments, including high-performance computing hardware and cloud-based platforms. The optimization techniques employed, such as the ADAM optimizer with different loss functions, are explained to highlight the thoroughness of the experimental approach. Additionally, the use of word clouds and confusion matrices provided a visual representation of the model's performance, aiding in the interpretation of results. Their findings demonstrate that BERT's comprehensive training and robust architecture enable superior performance in sentiment analysis tasks. The study concludes that pre-training the models on task-specific data further enhances accuracy, making BERT the preferred model for sentiment analysis in diverse datasets. This research underscores the potential of transformer-based models in handling complex sentiment analysis tasks and provides insights into optimizing these models for improved performance [7].

In an innovative study, Prasanthi and colleagues proposed a novel approach for sentiment analysis on social media using BERT and RoBERTa transformer-based models. The primary objective is to classify tweets based on sentiment, utilizing the advanced capabilities of these transformer models. Their methodology starts with pre-processing a large dataset of tweets to remove noise, tokenize text, and prepare it for analysis. BERT and RoBERTa are then fine-tuned on this dataset, leveraging transfer learning to adapt the models to the specific task of sentiment classification. These models' ability to capture contextual information and understand the relationships between words enhances the accuracy of sentiment analysis, especially with the informal language typical of social media platforms. Experimental results show that both BERT and RoBERTa significantly outperform traditional sentiment analysis models. BERT achieved high accuracy in sentiment classification, demonstrating its robustness and efficiency. RoBERTa, with its enhanced training techniques, provided even better performance metrics, highlighting its ability to handle large datasets efficiently and adapt to new domains with minimal additional training. The study also explores the scalability of these models, emphasizing their potential to manage large volumes of data and their versatility in various applications. The comprehensive approach includes detailed analysis using visualization tools like word clouds and confusion matrices to evaluate model performance, revealing that RoBERTa offers more reliable sentiment classification. This research underscores the importance of using advanced transformer models like BERT and RoBERTa for sentiment analysis on social media. The findings suggest significant potential for these models to improve the accuracy and reliability of sentiment classification, providing deeper insights into public opinion and emotions expressed on platforms like Twitter. The study's approach can be extended to other social media platforms, offering a robust framework for future sentiment analysis research [6].

In a comprehensive study, Wang et al. explore sentiment classification using the RoBERTa model enhanced with data augmentation techniques. The primary aim is to improve sentiment classification accuracy on Chinese comments by leveraging the unique capabilities of RoBERTa and addressing data limitations through augmentation. The methodology involves collecting datasets from Chinese microblog platforms, preprocessing the text data, and applying various data augmentation techniques to expand the dataset. RoBERTa, known for its robust semantic understanding, is then fine-tuned on this augmented dataset. The study utilizes the Nlpcc2013 and Nlpcc2014 datasets, focusing on binary sentiment classification tasks. Experimental results demonstrate that RoBERTa outperforms traditional models like TextCNN, BiLSTM, and BiGRU in both accuracy and F1-score. Specifically, RoBERTa achieved an accuracy of 86.84% on the Nlpcc2013 dataset and 90.03% on the Nlpcc2014 dataset. The study also includes a detailed ablation analysis to assess the impact of training set size on model performance. It was found that increasing the training set size significantly enhances the model's performance metrics. Moreover, data augmentation techniques, such as EDA (Easy Data Augmentation) and back-translation, were implemented to address the limited data issue. The results indicate that these methods, when combined with RoBERTa, further improve classification performance, with back-translation showing slightly better results than EDA. This research underscores the effectiveness of RoBERTa in sentiment classification tasks and highlights the benefits of data augmentation in enhancing model performance. The findings suggest that RoBERTa, combined with effective data augmentation techniques, offers a robust solution for sentiment analysis in the context of Chinese comments, providing valuable insights for future research in this area [1].

A study by Kumar et al. from the R.V Institute of Technology and Management, Bangalore, delves into sentiment analysis of Twitter data related to the Russo-Ukrainian War using the RoBERTa model. The primary goal is to classify tweets into negative, positive, and neutral sentiments to understand public opinion during the conflict. The research methodology involves the collection of over 300,000 tweets from March 2022 to October 2022 using advanced search filters and Python scripts for data scraping. The collected tweets are preprocessed to remove irrelevant information such as URLs, hashtags, and mentions. Non-English tweets are translated to English to maintain consistency. RoBERTa, a transformer-based model known for its deep learning capabilities, is then fine-tuned on this dataset to classify the sentiments. Experimental results indicate that the majority of tweets reflect negative sentiments towards the conflict. RoBERTa achieved an accuracy of 86.84% on the Nlpcc2013 dataset and 90.03% on the Nlpcc2014 dataset. The study includes a detailed analysis of monthly sentiment trends, revealing consistent negative sentiment over time. Additionally, the study compares RoBERTa's performance with BERT, showing that RoBERTa provides more confident and accurate sentiment classifications. This research highlights the effectiveness of using advanced NLP models like RoBERTa for sentiment analysis in high-stakes, real-time scenarios such as geopolitical conflicts. The findings suggest that RoBERTa's ability to handle large datasets and its nuanced understanding of context make it an invaluable tool for analyzing public opinion on social media [2].

A recent study by Jannatul Ferdoshi and colleagues from Brac University, Dhaka, presents an analysis of emotions and opinions expressed on Twitter using sentiment analysis techniques. The primary objective is to classify tweets into positive, negative, or neutral categories, employing both VADER and RoBERTa models. Their methodology involves gathering a dataset from the Mendeley Data repository and manually adding tweets covering various topics. The dataset undergoes preprocessing to remove noise, such as URLs, hashtags, and user mentions, while retaining essential textual content and emojis. VADER, a rule-based sentiment analyzer, and RoBERTa, a transformer-based model, are then used to analyze the sentiment of these tweets. Experimental results demonstrate that RoBERTa outperforms VADER in terms of accuracy, precision, recall, and F1-score. The study includes a comprehensive evaluation of both models using confusion matrices to provide a detailed performance comparison. The findings highlight the robust performance of RoBERTa in capturing contextual and semantic nuances, which are often missed by traditional lexicon-based approaches like VADER. This research underscores the value of employing advanced machine learning models for sentiment analysis on social media data. The study's approach offers a reliable tool for understanding public sentiment on Twitter, providing insights that can be valuable for various applications, including marketing, public relations, and social research [3].

Praveen Tumuluru and colleagues from Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India, propose an innovative ensemble classifier model for Twitter sentiment analysis, incorporating Transformer-XL, RoBERTa, and XGBoost. This study aims to leverage the strengths of these advanced NLP and machine learning models to enhance sentiment classification accuracy on Twitter data, especially considering the unique challenges posed by the platform's brevity, informal language, and frequent use of emoticons and hashtags. The methodology begins with collecting a diverse dataset of tweets, extending beyond COVID-19-related content, to ensure the model's versatility and generalizability across various domains and topics. The collected tweets are preprocessed to remove noise and prepare the text for analysis. Transformer-XL is used for its ability to capture long-range dependencies in sequential data, making it suitable for processing tweets. RoBERTa, a variant of BERT, is fine-tuned to enhance contextual word understanding, while XGBoost, a gradient-boosting framework, is employed to handle complex feature interactions. Experimental results indicate that the ensemble model outperforms individual classifiers, achieving higher accuracy, precision, recall, and F1 scores. Specifically, the proposed model demonstrates significant performance improvements, with an accuracy of 92.1%, precision of 77.3%, recall of 78.5%, and F1 score of 78.2%. The study also includes a detailed comparison of the ensemble model against standalone models, highlighting the superior performance of the ensemble approach. This research underscores the importance of integrating advanced NLP techniques and machine learning algorithms for sentiment analysis on social media. The findings suggest that the ensemble model can provide valuable insights into public sentiments, benefiting applications such as market analysis, brand perception monitoring, and social trend tracking. By harnessing the capabilities of Transformer-XL, RoBERTa, and XGBoost, the study contributes to advancing sentiment analysis techniques and improving the understanding of user sentiments on Twitter [4].

In a detailed investigation, Md. Nazmul Abdal and colleagues from Khulna University, Jahangirnagar University, and East West University introduce a robust method for Twitter sentiment analysis using the RoBERTa transformer-based model. The study aims to improve sentiment classification accuracy on Twitter by leveraging the advanced capabilities of RoBERTa, especially given the platform's unique characteristics, such as brevity, informal language, and the frequent use of slang and emojis. The methodology starts with the collection of a substantial dataset of tweets, followed by preprocessing to eliminate noise such as URLs, hashtags, and user mentions. The RoBERTa model is fine-tuned on this dataset, capitalizing on its ability to capture intricate contextual information and semantic nuances. The performance of RoBERTa is compared with other standard machine learning and deep learning models, including Decision Tree (DT), Support Vector Machine (SVM), and Long Short Term Memory (LSTM). Experimental results highlight that the RoBERTa model surpasses other models, achieving a remarkable accuracy of 96.78%. The study provides a comprehensive evaluation using various metrics such as precision, recall, F1-score, and ROC AUC score, emphasizing RoBERTa's superior performance. Furthermore, the research delves into the impact of different hyperparameter configurations on model performance, ensuring robustness and reliability. This research emphasizes the efficacy of RoBERTa in addressing the challenges of Twitter sentiment analysis. The findings suggest that RoBERTa's nuanced understanding of context makes it an invaluable tool for analyzing public sentiments on social media. The approach outlined in this study lays a strong foundation for future sentiment analysis work, offering valuable insights into the potential applications of transformer-based models in various fields, including marketing, public relations, and social research [5].

III. Dataset Description

The dataset used in this project is a publicly available dataset from https://data.world/datafiniti/hotel-reviews. This dataset contains a comprehensive collection of hotel reviews, including various attributes such as review text, review title, review ratings, and more.

A. Preprocessing

The dataset used in this project is a publicly available dataset from https://data.world/datafiniti/hotel-reviews. This dataset contains a comprehensive collection of hotel reviews, including various attributes such as review text, review title, review ratings, and more.

B. Preprocessing

The preprocessing of the dataset is performed using Python and the Pandas library to clean and prepare the data for input to the RoBERTa model. The following steps outline the preprocessing pipeline:

1) **Loading the Data:** The dataset is loaded into a Pandas DataFrame for easy manipulation and analysis.
2) **Removing Unnecessary Columns:** All columns are deleted except for `reviews.text` and `reviews.title`. These columns contain the actual review content and title, which will be merged to form the input to the transformer model.
3) **Handling Missing Values:** Any row with a null value in the `reviews.text` column is dropped from the dataset to ensure the quality of the input data.
4) **Removing Nonsensical and Foreign Language Reviews:** Reviews that are nonsensical (e.g., containing

only ”xxxxxxxxxxxxxxxxxxxxxxxxxxxxx”) or written in German are identified and removed from the dataset. This step ensures that the input data is relevant and meaningful for sentiment analysis.

5) **Merging Columns:** The `reviews.text` and `reviews.title` columns are merged into a single column. This combined text serves as the input for the sentiment analysis model.
6) **Setting the Target Variable:** The `reviews.rating` column is used as the target variable for the classification task, representing the review scores to be predicted, which are ratings ranging from 1 through 5.

C. Tokenization and Embeddings

For NLTK and VADER, tokenization and word embedding are crucial preprocessing steps. Tokenization involves splitting the text into individual words or tokens. NLTK provides various tokenizers, including the Punkt tokenizer, which is used to segment sentences. VADER, on the other hand, uses a lexicon-based approach where each token is matched against a predefined sentiment lexicon to determine its sentiment score.

RoBERTa uses subword tokenization (Byte-Pair Encoding) to handle the input text. The text is tokenized into subword units, which are then converted into embeddings by the model. This process allows RoBERTa to effectively manage large vocabularies and capture semantic nuances in the text.

D. Example Data

Figure 1 shows the first five rows of the dataset after preprocessing, including the combined review text and the target review rating.

Combined Review Text	**Review Rating**
`Pleasant 10 min walk along the sea front to the Water Bus. restaurants etc. Hotel was comfortable breakfast was good - quite a variety. Room aircon didn’t work very well. Take mosquito repelant!`	4
`It was a bit far from city center`	3
`Great hotel, staff where amazing and the location and views make this a great Base to visit Venice!`	5
`Perfect, best hotel over others in the area`	5
`Excellent Staff`	5

Fig. 1. First five rows of the preprocessed dataset.

The preprocessing steps ensure that the dataset is clean, standardized, and suitable for input to the RoBERTa model. By focusing on the review text and titles, the model can better understand the context and sentiment expressed in each review, leading to more accurate sentiment classification and review score predictions.

IV. Problem Statement

Accurate sentiment analysis is crucial for various applications in natural language processing (NLP). Traditional sentiment analysis techniques, such as lexicon-based models (e.g., NLTK and VADER), are commonly used to automate this process. While these models can provide general sentiment classification, they often fall short in capturing the nuanced and context-dependent sentiments expressed in reviews. This limitation can lead to inaccurate sentiment predictions, which in turn can affect the overall understanding of sentiment classification tasks.

Moreover, traditional models are typically designed for binary or ternary sentiment classification, making them inadequate for applications requiring more detailed sentiment categorization, such as predicting multi-class review scores. The inability to accurately classify reviews into specific star ratings (5-star, 4-star, 3-star, 2-star, and 1-star) can result in a loss of valuable information that could be used to improve services and understand customer satisfaction more deeply.

To address these challenges, this project aims to explore the use of advanced transformer-based models, specifically RoBERTa, for sentiment analysis of hotel reviews. RoBERTa’s robust capabilities in understanding context and capturing semantic nuances present an opportunity to improve the accuracy of sentiment classification. By comparing RoBERTa with traditional models such as NLTK and VADER, this project seeks to demonstrate the potential benefits of using transformer-based models for sentiment analysis in a multi-class classification task.

The primary objectives of this project are:

- To preprocess and standardize a large dataset of hotel reviews to ensure high-quality input for sentiment analysis.
- To fine-tune the RoBERTa model on the preprocessed dataset to accurately classify sentiments and predict review scores.
- To compare the performance of RoBERTa with traditional sentiment analysis models (NLTK and VADER) in terms of accuracy, precision, and F1-score.
- To assess the effectiveness of transformer-based models in a multi-class classification task.

This project aims to demonstrate that transformer-based models, specifically RoBERTa, can significantly enhance the accuracy of sentiment analysis for NLP applications and providing deeper insights into sentiment classification tasks.

V. Model Description

The RoBERTa model, short for ”Robustly optimized BERT approach,” is an advanced transformer-based model designed for a wide range of natural language understanding tasks, including sentiment analysis. RoBERTa is an extension of the BERT (Bidirectional Encoder Representations from Transformers) model, which is known for its bidirectional training of Transformer models.

A. BERT Model Overview

BERT is a transformer-based model that relies on a stack of encoders to build contextualized word representations. Each encoder consists of multi-head self-attention mechanisms and feed-forward neural networks. BERT's key innovation is its bidirectional approach, which allows it to capture context from both the left and right of each token in a sentence [17].

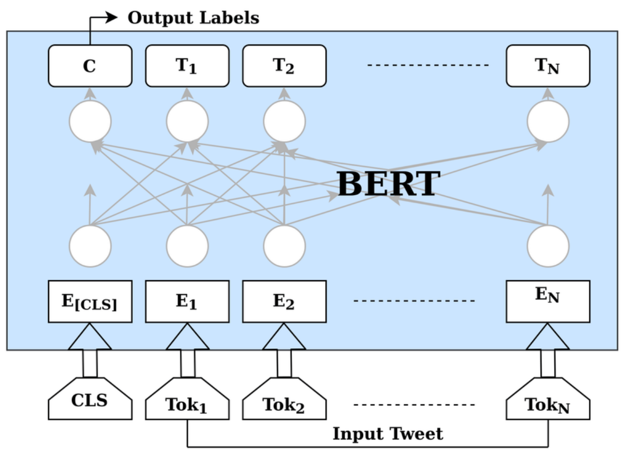

Fig. 2. Structure of the BERT Model for Sentiment Analysis [19]

Figure 2 shows the structure of the BERT model for sentiment analysis. The input embeddings consist of token embeddings, segment embeddings, and positional embeddings. These embeddings are fed into multiple layers of encoders, each containing self-attention and feed-forward layers. The output layer is used for classification tasks, such as sentiment analysis.

B. RoBERTa Model Overview

RoBERTa builds on BERT by incorporating several modifications and optimizations, including:

- Training with larger mini-batches and learning rates.
- Removing the next sentence prediction (NSP) objective.
- Training on a larger dataset with more steps.
- Dynamically changing the masking pattern during pre-training.

These improvements allow RoBERTa to achieve better performance across various NLP tasks, including sentiment analysis [18].

Figure 3 shows the structure of the RoBERTa model for sentiment analysis. The input embeddings are similar to BERT but optimized for better performance. The model consists of multiple layers of encoders with self-attention and feed-forward layers. The output layer is used for multi-class classification tasks, such as predicting review scores.

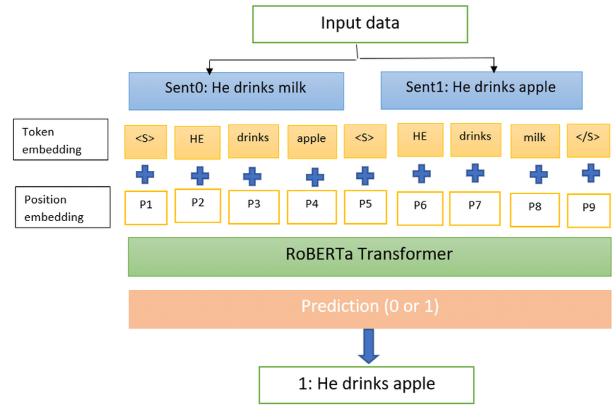

Fig. 3. Structure of the RoBERTa Model for Sentiment Analysis [20]

C. Fine-Tuning for Sentiment Analysis

To adapt RoBERTa for sentiment analysis of hotel reviews, the model undergoes a fine-tuning process. This involves the following steps:

1) **Preprocessing:** The hotel review text is tokenized using RoBERTa's subword tokenization (Byte-Pair Encoding). The tokenized text is converted into embeddings that serve as the model's input.
2) **Model Architecture:** RoBERTa's architecture includes multiple layers of encoders, each with self-attention mechanisms that allow the model to capture contextual information. The final layer produces a representation for each token, which is aggregated to form a single representation for the entire review.
3) **Classification Layer:** A fully connected layer is added on top of RoBERTa to classify the sentiment of each review. The model is fine-tuned using labeled hotel review data to optimize the classification layer for predicting review scores (1-star to 5-star).
4) **Training:** The model is trained using a cross-entropy loss function, with optimization performed using the Adam optimizer. The training process involves adjusting the model's weights to minimize the loss and improve classification accuracy.

The fine-tuning process allows RoBERTa to learn the specific nuances of hotel review sentiments, leading to improved performance in predicting review scores compared to traditional sentiment analysis models.

REFERENCES

[1] X. Wang, S. Xue, J. Liu, J. Zhang, J. Wang, J. Zhou, "Sentiment Classification Based on RoBERTa and Data Augmentation," Proceedings of CCIS2023.

[2] N. P. Kumar, et al., "Sentiment Analysis of Russo-Ukrainian War using Twitter Text Corpus," Department of Information Science and Engineering, R.V Institute of Technology and Management, Bangalore, India, 2023.

[3] J. Ferdoshi, et al., "Unveiling Twitter Sentiments: Analyzing Emotions and Opinions through Sentiment Analysis on Twitter Dataset," Department of Computer Science and Engineering, School of Data and Sciences, Brac University, Dhaka, Bangladesh, 2023.

[4] P. Tumuluru, et al., "Advancing Twitter Sentiment Analysis: An Ensemble Approach with Transformer-XL, RoBERTa, and XGBoost," Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India, 2023.
[5] M. N. Abdal, et al., "A Transformer-Based Model for Twitter Sentiment Analysis using RoBERTa," Computer Science and Engineering Discipline, Khulna University, Khulna, Bangladesh, 2023.
[6] K. N. Prasanthi, R. E. Madhavi, D. N. S. Sabarinadh, B. Sravani, "A Novel Approach for Sentiment Analysis on Social Media using BERT and RoBERTa Transformer-Based Models," Department of Computer Science and Engineering, Lakireddy Bali Reddy College of Engineering (Autonomous), Mylavaram, India, 2023.
[7] A. Joshy, S. Sundar, "Analyzing the Performance of Sentiment Analysis using BERT, DistilBERT, and RoBERTa," Centre for Artificial Intelligence, TKM College of Engineering, Kollam, Kerala, India, 2023.
[8] B. Kumar, A. D'Souza Jacintha, S. Sunil, V. S. Badiger, "Sentiment Analysis for Products Review based on NLP using Lexicon-Based Approach and RoBERTa," Department of Computer Science, Presidency College, Bengaluru, India, 2024.
[9] A. H. Azeemi, A. Waheed, "Performance Analysis of VADER and RoBERTa Methods for Smart Retail Customer Sentiment on Amazon Go Store," Information Technology University, Lahore, Pakistan, 2024.
[10] J. Ferdoshi, et al., "Unveiling Sentiments: Analyzing Learners' Experience Using VADER and RoBERTa Models," Department of Computer Science and Engineering, School of Data and Sciences, Brac University, Dhaka, Bangladesh, 2023.
[11] "What Is Sentiment Analysis?" IBM, www.ibm.com.
[12] "Sentiment analysis," Wikipedia, en.wikipedia.org.
[13] "8 Applications of Sentiment Analysis," MonkeyLearn, www.monkeylearn.com.
[14] H.D. Sharma and P. Goyal, "An Analysis of Sentiment: Methods, Applications, and Challenges," Eng. Proc., 2023, 59(1), 68.
[15] S. Bird, E. Loper, and E. Klein, "Natural Language Processing with Python," O'Reilly Media, Inc., 2009.
[16] C.J. Hutto and E. Gilbert, "VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text," in Proc. 8th Int. AAAI Conf. Weblogs Soc. Media (ICWSM), Ann Arbor, MI, 2014, pp. 216-225.
[17] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proc. 2019 Conf. North American Chapter Assoc. Comput. Linguistics: Human Lang. Technol., Minneapolis, MN, USA, Jun. 2019, pp. 4171-4186.
[18] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "RoBERTa: A Robustly Optimized BERT Pretraining Approach," in Proc. 2019 Conf. Empirical Methods Natural Lang. Process. (EMNLP), Hong Kong, China, Nov. 2019, pp. 2455-2465.
[19] "BERT model architecture," ResearchGate. [Online]. Available: https://www.researchgate.net/publication/348214408/figure/fig2/AS:976491001159681@1609825005204/BERT-model-architecture.ppm
[20] "RoBERTa model architecture," ResearchGate. [Online]. Available: https://www.researchgate.net/profile/Heba-Aljarrah-2/publication/348754985/figure/fig1/AS:983989435265025@1611612771423/The-architecture-of-our-model.ppm