Sayeed, M. S. (2023) effectively analyzes the obstacles in sentiment analysis utilizing the BERT Model framework. The paper outlines important challenges, including misclassifications coming from incorrectly labeling data and the incorrect classification of emotions as neutral. Contradictory emotions inside sentences represent a significant issue, leading to situations getting incorrect negative labels even when positive sentiment keywords are present, therefore minimizing accurate sentiment categorization. Additionally, the study indicates a notable pattern: a lower accuracy score for neutral emotion compared to positive and negative emotions, consistent with broader research patterns. Zhang et al. (2023) explored aspect-based sentiment analysis (ABSA), with a focus on utilizing sentiment data to reveal sentiments at the aspect level. The study highlighted the importance of integrating sentiment knowledge into computational approaches for scrutinizing perspectives and explored potential benefits from syntactical information. However, it's essential to acknowledge that the research was limited to ABSA tasks such as Aspect term Extraction (AE), Aspect-oriented Opinion term Extraction (AOE), and Aspect-level Sentiment Classification (ASC), thus delineating the study's boundaries within the realm of sentiment analysis. Barry et al. (2021) used 300-dimensional word2vec embeddings in a variety of applications, integrating them with the Random Forests technique and unique embeddings. They used a strong dictionary-based model to effectively monitor changing emotional content in order to improve the way emotions are represented in emoji embeddings and refine their methods. The study appears to set itself apart by avoiding adherence to predetermined categories of emotions and instead emphasizing the modeling that reflects a wide emotional spectrum inside emoji embeddings. Their approach suggested autonomy from large-scale datasets, promising efficient modeling of emojis that appear both regularly and irregularly. However, given that emojis may express many emotions at once, the model has several drawbacks, such as its inability to fully represent the spectrum of emoji emotions. Additionally, using dictionary meanings as a guide may not always convey the intended emotional content of an emoji. This indicates some potential challenges in accurately capturing subtle emotional nuances in the semantics of emojis. Yang et al. (2022) proposed a sentiment analysis approach for microblog comments, utilizing a fine-grained attention mechanism to capture interactions between emojis and plain text. They employed ALBERT for word vector learning, integrated emoji2vec for bi-sense emoji embeddings, and calculated inter-emoji embeddings using a weighted average based on attention. However, a limitation is noted for cases with multiple emojis or a need for diversification. The study suggests incorporating finer details like sender's name or timestamp for improved sentiment analysis. Existing methods in sentiment analysis using emojis often employ coarse-grained mechanisms, neglecting intricate interactions between emojis and plain text in microblog comments. Liu et al. (2021) investigated the challenges caused by the diverse syntax and semantics of Chinese and the use of lexicons in sentiment analysis. The study highlighted the difficulty in accurately identifying personal emotions, exacerbated by rapid changes in internet slang, However, the study found the rule-based algorithm's accuracy unsatisfactory, especially in short internet micro-texts with limited emotional cues. Additionally, the research delved into supervised learning's use of classification algorithms to evaluate emojis' impact on sentiment recognition. It revealed that, in most cases, algorithms with emoji posts exhibited significantly higher accuracy than emoji-free posts, indicating the effectiveness of emojis as expanding features in improving sentiment analysis algorithm accuracy. In this study, (Cai et al., 2023) employs various methods to tackle challenges in Aspect-Based Sentiment Analysis (ABSA). The research emphasizes the need for large-scale multi-domain datasets and introduces models like Large Language Models (LLMs), generative models (BART, T5-Paraphrase), and non-generative models (BERT, BERT-CRF) to enhance ABSA capabilities. However, the study acknowledges limitations, including the reliance on small datasets from specific domains and the oversight of implicit aspects in ABSA datasets. These findings highlight the importance of addressing dataset limitations for improved model generalizability in ABSA tasks. In their study, Liu et al. (2020) introduce the Bert-BiGRU-Softmax deep learning model to tackle sentiment word disambiguation and polarity issues in e-commerce reviews. The model employs the Bert model for feature extraction, a BiGRU model with attention mechanism for obtaining semantic codes, and a Softmax activation function for sentiment classification. The study also examines various sentiment analysis approaches, including lexicon-based methods, statistical measures like mutual information, and techniques such as Latent Semantic Indexing (LSI) and Principal Component Analysis (PCA). However, it is important to note that the proposed model was only tested on a large-scale dataset with over 500 thousand product reviews, which limits its generalizability to other datasets and domains. The authors suggest that future research should aim to extend the model's applicability to other contexts. Nguyen (2020) introduces two approaches to fine-tune BERT for sentiment analysis, incorporating Jacob Devlin's classification method and proposing a novel integration of BERT into three classification models. The study extensively compares these methods with other BERT fine-tuning approaches, with the goal of identifying the most effective model to complement BERT. However, it's important to note that the study's scope is limited to sentiment analysis of Vietnamese reviews. Therefore, the findings may lack generalizability to other languages or text types. Singh et al. (2022) explored LSTM for text data analysis alongside emojis, emphasizing the model's effectiveness in memorizing crucial information for classification tasks. The study introduced a dictionary approach for handling emojis within the Twitter tweet dataset and conducted a comprehensive comparison of sentiment-analysis methods for Twitter, encompassing supervised, unsupervised, and deep learning approaches. However, the research is limited to sentiment analysis within the Twitter data domain, potentially lacking generalizability to other social media platforms or data types. The accuracy of sentiment analysis is contingent upon data quality and pre-processing techniques, necessitating careful dataset selection and pre-processing considerations. Additionally, the use of emojis in sentiment analysis may be constrained by the availability of a comprehensive emoji lexicon and the model's ability to accurately interpret each emoji's meaning. Biesialska et al. (2021) evaluated a sentiment classifier model that relies on a self-attention mechanism and bi-attention, presenting advantages over traditional approaches by eliminating the need for manual preprocessing or feature selection. The study delved into various sentiment analysis approaches, encompassing lexicon-based methods utilizing pre-annotated word-lists and co-occurrence statistics-based techniques determining word polarity through co-occurrence calculations. However, a notable limitation of the proposed model is its testing on only three languages, each from a different language family, raising uncertainties about its performance on low-resource languages. Additionally, the fine-grained nature of sentiment analysis poses challenges for all models, including the one proposed. Ahanin et al. (2023) proposed and compared two deep learning-based methods for emotion classification in social media messages. The first model integrated hybrid features with a deep learning model (Bi-LSTM) featuring the Attention mechanism, while the second model incorporated the Transformer model (BERT) with Bi-LSTM. Experimentation demonstrated that the inclusion of hybrid features with deep learning models enhanced the prediction of emotion labels. The study also provided a literature survey on various methods used in sentiment analysis and emotion classification, including lexicon-based approaches, rule-based approaches, conventional machine learning, and deep learning techniques. However, a notable limitation of the proposed model is its data requirement, which may limit the detection of linguistic features. Additionally, the study did not explore the impact of different hyperparameters on the performance of the proposed model. Luo and Wang (2019) discuss the utilization of pre-trained word embeddings, sentence embeddings, and pre-trained language models like BERT. The authors fine-tuned their model to align with in-domain data, leading to high micro-F1 scores for the test sets of Friends and EmotionPush. However, there are some limitations, such as the low-resource problem in NLP and the requirement for additional resources to handle extremely low-resource data appropriately. The imbalanced data problem is also mentioned, along with the necessity for a large amount of supervised data to effectively learn numerous model parameters. Singh et al. (2022) employed an attention-based multi-task learning framework for emoji, sentiment, and emotion analysis, showcasing enhanced performance through joint task solving compared to separate solutions. The framework integrates sentiment and emotion information to predict emojis in a multi-task manner, utilizing various models such as a convolutional neural network (CNN) for emoji classification and bidirectional long short-term memory (BiLSTM) networks for sentiment and emotion classification. The study's limitation resides in its dataset, limited to English tweets geolocalized in the United States, potentially constraining generalizability to other languages and regions. Despite recognizing the challenge of emotion classification, the authors highlight the advantages of training a neural network jointly for both emotion and sentiment tasks.