SENTIMENT ANALYSIS OF ELECTRIC VEHICLE DISCOURSE USING BERT-BASED LANGUAGE MODEL

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CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provide an overview in reviewing the most recent literature from year 2020 to years 2025 in natural language processing (NLP) related studies. Reviews on what previous NLP model had been implemented for the NLP tasks such as social media sentiment analysis and text mining and which models performed better for the tasks. NLP model such as machine learning model, classical deep learning model, transformer-based language model and advanced NLP model such Large Language Model (LLM). This chapter is aim to underscore the significance and challenges of current social media discourse analysis especially in domain of electric vehicle, hence, detailed critical analysis of recent advancements and methods in these areas is presented, with a focus on current research trends and existing gaps.

2.2 Machine Learning Approach for Social Media Analysis

The machine learning models performed well in analyzing large amount of data and identifying pattern underlying the data. As it is able to understand nuanced and indirect language such as idioms, sarcasm and context specific meaning by train and learn from patterns in a large text dataset (Du et al., 2023).

2.2.1 Support Vector Machine (SVM)

Support vector machine (SVM) classifier is able to be implemented for sentiment analysis for clarifying text data into positive, negative and neutral sentiment. In research by Hussein et.al. (Hussein & Lakizadeh et.al.,2025), SVM performed rather well with an accuracy of 74.96% in classifying Iraqi text data into 3 different sentiment categories.

In addition, research in classifying another language text data which is Urdu Language was proposed by (Azim et al., 2025). In this research SVM correctly classify the sentiments with an accuracy of 87%.

2.2.2 Random Forest algorithm (RF)

Sentiment analysis research in examining public perception about STEM education and artificial intelligent is conducted by Smith-Mutegi et.al (Smith-Mutegi et.al, 2025) using machine learning based approach. In this study random forest algorithm is implemented in analyzing historical post containing terms of STEM and artificial intelligent obtaining through web crawling. The random forest able to classify the sentiment with an accuracy of 84.28%.

2.2.3 Logistic Regression (LR)

In a comparison of methodology for sentiment analysis, Logistic Regression (LR) effectively utilizing with TF-IDF matrix for determining patterns in the text. It performed relatively well with an accuracy of 74.82% in classify sentiment categories as compared to KNN of 50.78% (Hussein & Lakizadeh et.al.,2025). LR also performed well in sentiment identification for the tweet and IMDB movie review data with an accuracy of 87%. It obtains better results as compared to the deep learning model of LSTM and Bi-LSTM.

2.2.4 K-Nearest Neighbor (KNN)

K-Nearest Neighbors (KNN) had a limitation of high dimensional and sparse feature space causing it obtained a relatively poor performance as compared to other machine learning algorithm of LR and SVM. A relatively lowest accuracy result of 50.78% (Hussein & Lakizadeh et.al.,2025)

Table 2.1 below show the comparison of traditional machine learning model performance in social media sentiment analysis.

Table 2.1 Traditional Machine Learning Model Comparison

Author(s)	Dataset	Methodology	Performance
Smith-Mutegi et.al, 2025	33,379 historical posts from X application	Random Forest algorithm	accuracy: 84.28%
Hussein & Lakizadeh et.al.,2025	IRAQIDSAD corpus: - 14,141 annotated comments collected from four common Facebook page site of Iraqi	ML models using TF-IDF matrix: - Support Vector Machine (SVM) - Logistic Regression (LR) - K-Nearest Neighbours (KNN)	- Support Vector Machine (SVM): 74.96% - Logistic Regression (LR): 74.82% - K-Nearest Neighbours (KNN): 50.78%
Azim et al., 2025	Urdu Twitter reviews and IMDB movie reviews datasets which obtained from Kaggle	- Support vector machine (SVM) - Logistic Regression (LR)	Both models obtain accuracy of: 87%
(Xu, Wen, Zhong, & Fang, 2025)	17,720 deepfake-related posts and comments on the Reddit	six machine learning model: Logistic Regression(LR), Random Forest(RF), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree, and Naive Bayes	Accuracy: - Logistic Regression: 78.92% - Random Forest: 78.49% - K-Nearest Neighbors (KNN): 76.97% - Support Vector Machine (SVM): 78.70% - Decision Tree: 76.00% - Naive Bayes: 76.54%
Smith-Mutegi et.al, 2025	33,379 historical posts from X application	Random Forest algorithm	accuracy: 84.28%

2.3 Deep Learning Approach for Social Media Sentiment Analysis

This section shows the most recent research that are relevant to sentiment analysis using deep learning techniques. The purpose of this section is to find out the most used deep learning model that can perform better than traditional machine learning model.

2.3.1 Convolutional Neural Network (CNN)

A hybrid model CNN-LSTM is used to reflect contextual subtleties of the text, which could help to identify short term pattern such as n-gram recognition in a text and long-term meaning in a text, which making sentiment analysis more accurate. However, in order to reduce the computational complexity of LSTM, a hybrid model of CNN-GRU is also been implement for comparison as GRU model has a simplified architecture. In the research done by Hussein et.al. (Hussein & Lakizadeh et.al.,2025) show that the result of comparison for both hybrid CNN model of CNN-LSTM and CNN-GRU has an accuracy of 74.34% and 74.21%. CNN-LSTM and CNN-GRU performance is slightly similar.

2.3.2 Bidirectional Long Short-Term Memory (Bi-LSTM)

Bidirectional Long Short-Term Memory (Bi-LSTM) is capable to deal with data which has long term dependencies in the sentences (Wei et.al, 2020). As proposed by Mahadevaswamy et.al. (Mahadevaswamy et.al., 2023) stated that the Bi-LSTM had a memory in the model for it to make better prediction. The proposed model can successfully classify the reviews into positive and negative categories with an accuracy of 91.4%. Besides that, a Bi-LSTM approach was also proposed to classify twitter and IMBD movies review in Urdu language and as a comparison of which classification model performed well. The result shows that the Bi-LSTM approach achieve an accuracy result of 84% (Azim et al., 2025).

In addition, Mao et.al, 2023 (Mao et.al, 2023) also proposed an Information Blocks Bidirectional Long-Short term Memory (IB-BiLSTM) model in capturing the sentiment analysis of animated online education texts from students. The model is design to able to capture temporal correlations and long-range dependencies in text data obtain from online animated education. The model shows a compromising result with an accuracy of 93.92%. Proving that implication of multimodal data for emotion recognition can improve sentiment classification.

2.3.3 Long Short-Term Memory (LSTM)

A standalone LSTM model in research study of Hussein et.al. (Hussein & Lakizadeh et.al.,2025) had a comparative lower accuracy as compared to other hybrid deep learning model in classifying sentiment analysis on Iraqi dialect. It achieves a accuracy of 68.26% showing the necessity of enhancement for the architecture. However, a standalone LSTM model in identify sentiment analysis for Urdu language's tweet data and IMDB movie review data had a rather well accuracy of 84% (Azim et al., 2025).

In addition, a hybrid model combining Recurrent Neural Network (RNN)-based Long Short-Term Memory (LSTM) classifier with Bi-directional Gated Recurrent Units (BiGRU) for feature extraction is proposed by (Atlas et al., 2025) for classifying sentiment of product review in e-commerce domain. The accuracy result of 98.79% show that the proposed model is effective in capturing word level meaning and meaning across long term dependencies.

Table 2.2 below shows the comparison of deep learning model performance in social media sentiment analysis.

Table 2.2 Deep Learning Model Comparison

Author(s)	Dataset	Methodology	Performance
Atlas et al., 2025	50,253 fashion products reviews from Amazon website	Recurrent Neural Network (RNN)-based Long Short-Term Memory (LSTM)	Accuracy: 98.79 % Precision: 96.64 Recall: 98.7 F1-score:97.43 Auc:99.2

Mao et.al, 2023	Student feedback text data, emotional text data, writing text data, and verbal expression text data	information blocks Bidirectional Long-Short term Memory (IB-BiLSTM)	Accuracy: 93.92% F1-score: 90.34%
Mahadevaswamy et.al, 2023	Amazon Product Review dataset: 104,975 product review	Bidirectional LSTM network	Accuracy: 91.4%
Hussein & Lakizadeh et.al.,2025	IRAQIDSAD corpus: - 14,141 annotated comments collected from four common Facebook page site of Iraqi	- Convolutional Neural Networks with Long Short-Term Memory (CNN-LSTM) - Convolutional Neural Networks with Gated Recurrent Unit called as (CNN-GRU) and - Long Short-Term Memory (LSTM)	Accuracy for each model: - CNN-LSTM: 74.34% - CNN-GRU: 74.21% - LSTM: 68.26%
Azim et al., 2025	Urdu Twitter reviews and IMDB movie reviews datasets which obtained from Kaggle	- Long Short-Term Memory (LSTM) - Bidirectional Long Short-Term Memory (Bi-LSTM)	Both model Accuracy: 84%

2.4 Ensemble learning Approach for Social Media Sentiment Analysis

This section provides an overview in implementation of ensemble learning towards sentiment analysis. Ensemble learning is a technique which combined multiple classifiers to improve accuracy and handling dynamic data. Azim et al. (Azim et al., 2025) proposed a ensemble model to identify sentiment of Urdu Twitter reviews and IMDB movie reviews. An ensemble classifier model named RRLS which is stacks of machine learning and deep learning model consisting Random Forest (RF), Recurrent Neural Network, Logistic Regression (LR), and Support Vector Machine (SVM). The ensemble model in this study is well performed as compared to the other standalone machine learning classifier of SVM, LR, and deep learning model of LSTM and Bi-LSTM. It achieved an accuracy of 90%, but when synthetic minority oversampling technique (SMOTE) is implemented the performance of accuracy increased 2.77%. However, ensembled learning required high computational complexity, hence the future work on enhancing RRLS model using lightweight structured model.

Table 2.3 below show the comparison of ensemble model performance toward social media sentiment analysis.

Table 2.3 Ensemble Learning model table

Author(s)	Dataset	Methodology	Performance
Azim et al., 2025	Urdu Twitter reviews and IMDB movie reviews datasets which obtained from Kaggle	Stacks of Random Forest (RF), Recurrent Neural Network, Logistic Regression (LR), and Support Vector Machine (SVM)	Accuracy without SMOTE: 90% Accuracy with SMOTE: 92.77%

2.5 Transformer-Based/ Large Language Model Approach for Sentiment Analysis

This section shows the implementation of pre-trained BERT-based model approach in previous research for sentiment analysis. Comparison of the BERT-based model and advance BERT-based model is show in this section.

2.5.1 Bidirectional Encoder Representations from Transformers (BERT) model

BERT-based model is effective for sentiment analysis task as it able to capture global context using bidirectional encoder representation. Research proposed by Xu et.al., (Xu, et.al., 2025) implemented 3 BERT-based model to trained on annotated negative data to classify sentiment of anger, fear and sadness. Negative data on comment post at Reddit regarding deepfake perception. The BERTweet-based-sentiment-analysis performed better in identify the nuanced social media text with accuracy of 87.03%. Whereas the BERT-base-uncased-emotion obtain a accuracy of 84.76%, followed by accuracy of 84.32% for BERT-base-uncased.

In addition, a model named AraBERT that conducted in research studies by Hussein et.al. (Hussein & Lakizadeh, 2025) is a pretrained Arabic language model based on the BERT architecture. It was trained based on standard Arabic language and dialects with an aim to perform natural language processing as for English language. The model in this study were used to evaluate how well does this model performed for sentiment analysis on common four Iraqi dialects Facebook site pages. The results of the AraBERT outperformed all the others machine learning and deep learning model with an accuracy of 90.18%. This proven that BERT is efficient in language understanding.

2.4.2 Robustly Optimized BERT Approach (RoBERTa)

RoBERTa which is an improved version of BERT it had stronger pretrained capabilities, capable of handle large dataset and has more accurate prediction.

In order to improve the model performance of existing Bidirectional Encoder Representations from Transformers-Bidirectional Long Short-Term Memory (BERT-BiLSTM) model in issue regarding lengthy text and complex sentiment expression (Tiwari et.al, 2020), a hybrid RoBERTa model is proposed by Cao et.al (Cao et.al,2024). A hybrid RoBERTa-CNN-BiLSTM-Transformers (RCBT) model which combination of RoBERTa, CNN and Transformer. As CNN can enhance local feature extraction such as word combination, while Transformer can improve long range dependencies using self-attention without increase computational complex. The proposed model achieves a high accuracy of 93.46% in classifying IMDB movie review sentiment analysis.
Table 2.4 below shows the comparison of BERT based model used for social media sentiment analysis.

Table 2.4 BERT-based Model Comparison

Author(s)	Dataset	Methodology	Performance
Cao et.al,2024	IMDB movie reviews datasets officially provided by Stanford University: 50,000 reviews	- BERT-BiLSTM model - BERT-CNN-BiLSTM -BERT-CNN-BiLSTM- Transformer -RoBERTa-CNN-BiLSTM-Transformers	Accuracy for each model - BERT-BiLSTM model: 91.55% - BERT-CNN-BiLSTM: 92.03% -BERT-CNN-BiLSTM- Transformer: 92.30% -RoBERTa-CNN-BiLSTM-Transformers: 93.46%
Hussein & Lakizadeh, 2025	IRAQIDSAD corpus: - 14,141 annotated comments collected from four common Facebook page site of Iraqi	AraBERT	Accuracy: 90.18%
(Xu, Wen, Zhong, & Fang, 2025)	17,720 deepfake-related posts and comments on the Reddit	3 BERT-based models: - BERT-based-uncased - BERT-based-uncased- emotion - BERTweet-based-sentiment-analysis	Accuracy: - BERT-base-uncased: 84.32% - BERT-base-uncased-emotion: 84.76% - BERTweet-based-sentiment-analysis: 87.03%
Cao et.al,2024	IMDB movie reviews datasets officially provided by Stanford University: 50,000 reviews	- BERT-BiLSTM model - BERT-CNN-BiLSTM -BERT-CNN-BiLSTM- Transformer -RoBERTa-CNN-BiLSTM-Transformers	Accuracy for each model - BERT-BiLSTM model: 91.55% - BERT-CNN-BiLSTM: 92.03% -BERT-CNN-BiLSTM- Transformer: 92.30% -RoBERTa-CNN-BiLSTM-Transformers: 93.46%

2.5 Recent Studies on Electric Vehicle Sentiment Analysis Approach

Sharma et.al. (Sharma, Din, et.al.,2024) investigated sentiment analysis on electric vehicles (EVs) using advanced pre-trained transformer models of BERT, XLNet and RoBERTa. XLNet is choosen as improvement of BERT's masked language model which combining autoregressive and autoencoding modelling (Song, Tan, Qin, Lu, & Liu, 2020). Based on the sentiment on YouTube comments related to Tesla and Lucid Motors. RoBERTa emerged as the best-performing model, achieving an accuracy of 92.33% for Lucid datasets while BERT performed well with an accuracy of 93.63% for Tesla datase. While the study demonstrates the efficacy of large language models (LLMs) in EV discourse analysis, its reliance on small, platform-specific datasets introduces potential bias. The authors acknowledged this limitation and proposed expanding the research to other platforms like Twitter while enhancing data quality through expert annotations. This study sets a foundational benchmark in applying transformer-based models in EV sentiment analysis and encourages future research to adopt diversified datasets and platforms for broader generalization.

Similarly focusing on sentiment detection, Wang et al. (2023) combined ERNIE, a knowledge-enhanced language model, with a convolutional neural network (CNN) to analyze online comments about new energy vehicles (NEVs). Their hybrid approach achieved a notably high accuracy of 97.39%. However, the study's sentiment classification was constrained to basic categories, limiting its depth in sentiment granularity. Their future direction includes the integration of more nuanced model fusion methods and the simplification of model parameters, offering a pathway toward more efficient and expressive sentiment detection.

Wu et al. (Wu et.al.,2023) conducted on research by applying Latent Dirichlet Allocation (LDA) for topic modeling and sentiment analysis through the Natural Language Processing tools of NLPIR-Parser to study public opinions on Sina Weibo, a popular Chinese social media platform. Their findings highlighted specific NEV-related topics such as preferential policies and user sentiment (positive or negative) surrounding them. Despite offering valuable insights into Chinese social discourse on NEVs, the study lacked comparative analysis with international platforms, suggesting the potential for cross-cultural sentiment comparisons and policy benchmarking in future research. This comparative angle could tie in meaningfully with Sharma et al. (2024), who also emphasized dataset diversity and platform inclusiveness.

In addition, another research was also focusing on policy sentiment. Research by Wibowo et.al. (Wibowo et.al., 2023) explored Indonesian public reactions towards electric vehicle tax incentives through tweets data. An Indonesian RoBERTa-based sentiment classifier is proposed in this study for public reaction sentiment classification. The proposed model achieved a accuracy of 71.81%, highlighting there is still room for methodological improvement. The study's narrow geographic and platform focus limited its broader applicability. Future work intends to expand to other social media platforms, offering an opportunity for more comparative or regional sentiment analyses, especially in line with studies like (Wu et.al.,2023) and (Sharma, Din, et.al.,2024) that proposed in the future work for cross-platform exploration.

Özkara et al. (Özkara et al., 2025) examined social media discourse on electric vehicle by leveraging LSTM and LDA models on English and Turkish tweets from Platform X application. The LSTM model obtain with a high accuracy rates of 96.7% for Turkish and 92.1% for English, the study provides evidence for LSTM's robustness in sentiment detection across multilingual data. However, the research was constrained by only crawling for one-month tweets data window and there were also potential demographic biases due to platform user characteristics were simplicity. Hence, in future work, the authors recommended incorporating BERT-based models for enhance sentiment identification in multilingual contexts and extending analyses across longer timelines and additional platforms such as Reddit and Instagram. This aligns with (Sharma, Din, et.al.,2024) and (Cui et al., 2025). who highlighted the value of incorporating broader social media data to enrich sentiment insights.

Cui et al. (Cui et al., 2025) contributed a novel perspective by analyzing 2818 short video interviews on TikTok with 2,101 of electric vehicle users in Beijing. The

Latent Dirichlet Allocation (LDA) Model is used for topic modelling, while Baidu's Large Language Model (LLM), and Random Forest models facilitated the extraction of sentiment for different themes. The LLM achieving 95% accuracy for automobile sentiment evaluation of positive, negative and neutral. Whereas the random forest model is best fit in this study with R-squared (R^2) of 0.8668 for female and 0.8706 for male, whereas Mean Absolute Error (MAE) of 0.1384 for female and 0.1256 for male. Despite its innovation, the study's limitations included geographic and demographic constraints, potential bias from non-random sampling, and challenges in nuanced sentiment recognition for sarcasm. The authors proposed incorporating more platforms and multimodal data to fill current analytic gaps. The study's focus on short video content and multimodal analysis potential aligns conceptually with (Liu et al., 2025), who also advocate for richer data formats beyond text.

Liu et al. (Liu et al., 2025) proposed quantitative economic research by forecasting EV sales using a hybrid BERT-Bi-LSTM model. Drawing from monthly sales data, forum posts, and gasoline prices, the model achieved an accuracy of 94%, showing strong predictive power. However, limitations arise from inadequate factor selection, incomplete data decomposition, and the lack of multimodal data integration. Future directions include incorporating videos, images, and performing outlier analysis to capture sudden market shifts. This study complements (Cui et al., 2025) in its call for multimodal data analysis and bridges sentiment analysis with predictive economic modeling—broadening the scope of EV-related research.

While not directly EV-related, the study by Pascal et.al. (Pascal et.al., 2025) introduced a deep learning approach using EEG data to predict user behavior in electronic markets. The proposed SIEPTNet model used CNNs to predict all five personality traits from EEG data, showing improved accuracy performance with Gaussian filtering. Despite not being situated within the EV domain, the methodology's potential in capturing cognitive or emotional user responses to EV-related marketing or interfaces could complement sentiment studies like those by (Cui et al., 2025) or (Liu et al., 2025), especially if integrated into multimodal frameworks.

Intercorrelations among these studies highlight a trend toward multimodal data integration (Cui et al., Liu et al., 2025), cross-platform social media analysis (Sharma et al., Wu et al., Özkara et al.), and transformer model dominance in sentiment extraction (Sharma et al., Wang et al., Wibowo et.al.). There's a consistent emphasis on moving beyond textual data and basic sentiment classification, pushing toward nuanced, scalable, and contextually rich sentiment modeling frameworks. These efforts collectively contribute to a more comprehensive understanding of EV discourse and user perception, crucial for both industry decision-making and policy formulation.

Table 2.5 below shows the summary of recent study in electric vehicles towards sentiment analysis.

Table 2.5 Summary of electric vehicle sentiment research

Author(s)	Dataset	Methodology	Performance
Sharma, Din, et.al.,2024	Lucid Motors and Tesla Motors-related YouTube data	BERT, XLNet, and RoBERTa pre-trained transformer models	Accuracy for Tesla dataset: - BERT without Fine Tuning: 9.75% BERT with Fine Tuning: 93.63% - RoBERTa without Fine Tuning: 5.34 RoBERTA with Fine Tuning: 92.12% - XLNet without Fine Tuning: 42.26% XLNet with Fine Tuning: 90.10% Accuracy for Lucid dataset: - BERT without Fine Tuning: 37.06%

			BERT with Fine Tuning: 90.33% - RoBERTa without Fine Tuning: 17.30% RoBERTA with Fine Tuning: 92.33% - XLNet without Fine Tuning: 43.88% XLNet with Fine Tuning: 90.90%
Wang et al, 2023	dataset of new energy vehicle comments collected from multiple automotive social media platform	Hybrid model of Enhanced Representation through kNowledge IntEgration (ERNIE) and a deep (Convolutional Neural Network) CNN	accuracy rate of 97.39%
Wu et.al., 2023	Sina Weibo	- LDA topic modelling - Sentiment analysis is performed in the NLPIR-Parser platform	- positive, negative sentiment - on which NEV topic - preferential policies
Wibowo et.al., 2023	Twitter data	Indonesian RoBERTa-Based Sentiment Classifier	accuracy: 71.81%
Özkara et al., 2025	X social media platform - consists of 6000 English and 891 Turkish tweets	- Long short-term memory (LSTM) model - Latent Dirichlet Allocation (LDA)	Accuracy: - 96.7% for Turkish tweets - 92.1% for English tweets
Cui et al., 2025	2818 short videos about EV experience form Tiktok User named EV USERS UNION:	Text Modelling: - Latent Dirichlet Allocation (LDA) Model sentiment analysis: - LLM developed	- LLM: 95 % accuracy - Random Forest: For Female R^2: 0.8668

	street interviews by a TikTok user in Beijing which contain 41 hours length of video interviews with 2101 electric vehicle (EV) owners	by Baidu - Random Forest	MAE: 0.1384 For male R^2: 0.8706 MAE: 0.1256
Liu et al., 2025	forum text from Auto Home: Car owners homes and East Money Information to collect monthly data on electric vehicle sales and gasoline prices.	Bidirectional Encoder Representations from Transformers-Bidirectional long short-term memory (BERT-Bi-LSTM)	Accuracy: 94%
Pascal Penava & Buettner, 2025	LEMON Data which consist of electroencephalographic data - publicly available resting-state EEG data from 203 participants whose data was tagged using 62 digitized EEG channels.	CNN architecture called Subject-Independent EEG-based Personality Trait Network (SIEPTNet)	Average evaluation metrics over 10 folds without Gaussian filtering across all five personality traits - Openness: 0.6069 - Conscientiousness: 0.6400 - Extraversion: 0.6394 - Agreeableness: 0.6779 - Neuroticism: 0.6208 Average evaluation metrics over 10 folds with Gaussian filtering across all five personality traits - Openness: 0.6403 - Conscientiousness: 0.6398 - Extraversion: 0.6818

			- Agreeableness: 0.6874 - Neuroticism: 0.6539

2.7 Depth and Analysis

The above shows a progressive evolution in sentiment analysis techniques applied to electric vehicle (EV) discourse, ranging from of traditional machine learning model, to deep learning model, ensemble model approach and transformer-based approach. There is sentiment analysis approaches implementing traditional machine learning algorithms such as Naive Bayes and Support Vector Machines (SVM), but there is a limitations in handling complex linguistic contexts. These traditional methods, while foundational, often lacked the semantic depth needed to capture nuanced sentiment, particularly in large and diverse datasets. Ensemble learning approaches then sought to mitigate these limitations by integrating multiple algorithms to improve accuracy and robustness. Studies employing voting classifiers, Random Forests, and hybrid frameworks like CNN-LSTM and Bi-LSTM-Attention demonstrated significant gains in performance, particularly in capturing contextual dependencies. However, they still struggled with language ambiguity and required extensive feature engineering, which constrained scalability across different datasets and platforms.

The shift towards deep learning and especially transformer-based models marks a major turning point in the field. BERT and its variants such as RoBERTa, XLNet and ERNIE consistently outperform earlier methods by leveraging contextual embeddings and deep bidirectional understanding of language. Transformer models, as shown in the studies by Sharma et al., Wang et al., and Wibowo et al., not only improve sentiment classification accuracy but also facilitate cross-lingual and domain-specific adaptation. The integration of domain knowledge, as in ERNIE’s case, and the inclusion of platform-specific nuances such as Twitter, YouTube, and Sina Weibo had underscored the importance of tailoring sentiment analysis tools to the characteristics of both the data and the user base. However, challenges still remain. Challenges in ensuring dataset diversity across diverse social media platform.

Recent literature studies further emphasize the implementation of multimodal approach and sentiment analysis on cross-platform. The application of Latent Dirichlet Allocation (LDA) for topic modeling, which used by Wu et al. and Cui et al., reflects an effort to contextualize sentiment within broader discourse themes such as policy, environmental awareness, or economic concerns. These topic models provide a overview on which sentiments are better understood in relation to public concerns. Additionally, the integration of models like Random Forests and even EEG-based CNN frameworks in the study by Pascal et al. signals a move toward interdisciplinary approaches, combining behavioral insights with computational methods to enrich sentiment interpretation. Furthermore, the studies highlight a growing interest in video-based and multimodal data—such as those from TikTok and sales forecasts—where sentiment is inferred not just from text but also visual, behavioral, and contextual cues.

Overall, there is a clear trajectory toward more holistic, context-aware, and technologically sophisticated sentiment analysis approaches in the EV domain. Transformer-based architectures dominate current methodologies due to their scalability and performance, yet there is a consistent call across studies for enhanced generalizability, multimodal integration, and real-time applicability. The field is steadily moving beyond surface-level polarity classification toward deeper understanding of consumer perception, emotional resonance, and market dynamics—all of which are critical for informing EV-related policy decisions, marketing strategies, and user-centered technological development.

2.8 Conclusion

In conclusion, the findings from the literature review have provided valuable insights into the sentiment analysis and electric vehicle projects. It summarize recent articles and the baseline papers from scholarly articles to this project with conducting some analysis on the previous research. From this chapter the sentiment analysis model approach is shown in table 2.1 until 2.4. Besides that the tabulation of sentiment analysis particular for the domain of electric vehicle is shown in the table 2.5. From the review, shown there is existing gap highlighting the opportunities for future research to explore more inclusive which were further proposed as the research gap in this research.

REFERENCES

Atlas, L. G., Arockiam, D., Muthusamy, A., Balamurugan Balusamy, Shitharth Selvarajan, Taher Al-Shehari, & Alsadhan, N. A. (2025). A modernized approach to sentiment analysis of product reviews using BiGRU and RNN based LSTM deep learning models. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-01104-0

Azim, K., Tahir, A., Mobeen Shahroz, Hanen Karamti, Vazquez, A. A., Vistorte, A. R., & Ashraf, I. (2025). Ensemble stacked model for enhanced identification of sentiments from IMDB reviews. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-97561-8

Cao, J. (2024). An improved RCBT model and its application to sentiment analysis of movie comments. 1016–1023. https://doi.org/10.1109/ispcem64498.2024.00180

Cui, Q., Zhang, Y., Ma, H., Zhang, K., Peng, J., Chen, Z., … Lin, Z. (2025). How about electric vehicle? Sensing owners' experiences and attitudes through online short video. Transport Policy, 167, 1–15. https://doi.org/10.1016/j.tranpol.2025.03.012

Du, J., Mamo, Y. Z., Floyd, C., Karthikeyan, N., & James, J. D. (2023). Machine Learning in Sport Social Media Research: Practical Uses and Opportunities. International Journal of Sport Communication, 17(1), 97–106. https://doi.org/10.1123/ijsc.2023-0151

Hussein, H. H., & Lakizadeh, A. (2025). A systematic assessment of sentiment analysis models on iraqi dialect-based texts. Systems and Soft Computing, 7, 200203. https://doi.org/10.1016/j.sasc.2025.200203

Liu, J., Pan, H., Luo, R., Chen, H., Tao, Z., & Wu, Z. (2025). An electric vehicle sales hybrid forecasting method based on improved sentiment analysis model and secondary decomposition. Engineering Applications of Artificial Intelligence, 150, 110561–110561. https://doi.org/10.1016/j.engappai.2025.110561

Mao, J., Qian, Z., & Lucas, T. (2023). Sentiment Analysis of Animated Online Education Texts Using Long Short-Term Memory Networks in the Context of the Internet of Things. IEEE Access, 11, 109121–109130. https://doi.org/10.1109/access.2023.3321303

Mahadevaswamy, U. B., & Swathi, P. (2023). Sentiment Analysis using Bidirectional LSTM Network. Procedia Computer Science, 218, 45–56. https://doi.org/10.1016/j.procs.2022.12.400

Özkara, Y., Bilişli, Y., Yildirim, F. S., Kayan, F., Başdeğirmen, A., Kayakuş, M., & Yiğit Açıkgöz, F. (2025). Analysing Social Media Discourse on Electric Vehicles with Machine Learning. Applied Sciences, 15(8), 4395. https://doi.org/10.3390/app15084395

Penava, P., & Buettner, R. (2025). A novel subject-independent deep learning approach for user behavior prediction in electronic markets based on electroencephalographic data. Electronic Markets, 35(1). https://doi.org/10.1007/s12525-025-00778-8

Song, K., Tan, X., Qin, T., Lu, J., & Liu, T.-Y. (2020). MPNet: Masked and Permuted Pre-training for Language Understanding. Retrieved May 22, 2025, from arXiv.org website: https://arxiv.org/abs/2004.09297

Smith-Mutegi, D., Mamo, Y., Kim, J., Crompton, H., & McConnell, M. (2025). Perceptions of STEM education and artificial intelligence: a Twitter (X) sentiment analysis. International Journal of STEM Education, 12(1). https://doi.org/10.1186/s40594-025-00527-5

Tiwari, P., Mishra, B. K., Kumar, S., & Kumar, V. (2020). Implementation of n-gram Methodology for Rotten Tomatoes Review Dataset Sentiment Analysis. IGI Global EBooks, 689–701. https://doi.org/10.4018/978-1-7998-2460-2.ch036

Wang, M., You, H., Ma, H., Sun, X., & Wang, Z. (2023). Sentiment Analysis of Online New Energy Vehicle Reviews. Applied Sciences, 13(14), 8176–8176. https://doi.org/10.3390/app13148176

Wei, J., Liao, J., Yang, Z., Wang, S., & Zhao, Q. (2020). BiLSTM with Multi-Polarity Orthogonal Attention for Implicit Sentiment Analysis. Neurocomputing, 383, 165–173. https://doi.org/10.1016/j.neucom.2019.11.054

Wibowo, A. S., & Septiari, D. (2023). How Does the Public React to the Electric Vehicle Tax Incentive Policy? A Sentiment Analysis. Journal of Tax Reform, 9(3), 413–429. https://doi.org/10.15826/jtr.2023.9.3.150

Wu, Z., He, Q., Li, J., Bi, G., & Antwi-Afari, M. F. (2023). Public attitudes and sentiments towards new energy vehicles in China: A text mining approach. Renewable and Sustainable Energy Reviews, 178, 113242–113242. https://doi.org/10.1016/j.rser.2023.113242

Xu, Z., Wen, X., Zhong, G., & Fang, Q. (2025). Public perception towards deepfake through topic modelling and sentiment analysis of social media data. Social Network Analysis and Mining, 15(1). https://doi.org/10.1007/s13278-025-01445-8