Sr. No.	Title of the Paper	Name of the Authors	Publishe d Year	Remarks/Findings
1	A Study of Profanity Effect in Sentiment Analysis on Natural LanguageProcessing Using ANN	Cheong-Ghil Kim, Young- Jun Hwang1 and Chayapol Kamyod	2002	<ul> <li>used a deep learning model, specifically an LSTM (Long Short-Term Memory) model, to check how profanity affects sentiment analysis using machine learning in written text. They also mentioned the use of the Transformer model, which includes the BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer)</li> <li>Automatic Feature Extraction: Deep learning models can automatically extract complex features from text data, eliminating the need for manual feature engineering.</li> <li>Training Complexity: Deep learning models, especially Transformer models, can be computationally intensive to train due to the large number of parameters and the need for extensive computational resources.</li> </ul>
2	Deep Learning for Automated Sentiment Analysis of Social Media	Li-Chen Cheng Song-Lin Tsai	2019	<ul> <li>The researchers used a Python crawler in the first module to collect review data from sources such as YouTube and Facebook</li> <li>Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM), and Gated Recurrent Units (GRUs). These algorithms were employed to build deep-learning based sentiment classification models for analyzing sentiment in social media language.</li> <li>They can handle the informal and slang-filled nature of social media language, allowing for more accurate sentiment analysis.</li> <li>Deep learning models can be complex and computationally intensive, requiring substantial resources for training and inference.</li> </ul>

3	COVID-19 Sensing: Negative Sentiment Analysis on Social Media in China via BERT Model	Tianyi Wang, Ke Lu, Kam Pui Chow, and Qing Zhu	2020	<ul> <li>Bidirectional Encoder Representations from Transformers (BERT) model, which is a neural network-based technique for natural language processing pretraining, was employed for sentiment analysis.</li> <li>the study utilized the TF-IDF (term frequency-inverse document frequency) model to summarize the topics of the Weibo posts</li> <li>In the study, the BERT model achieved a high accuracy of 75.65% for sentiment classification, surpassing many NLP baseline algorithms.</li> <li>BERT is a complex model with a large number of parameters, which can make it computationally intensive and resource-consuming.</li> </ul>
4	Sentiment Analysis of Public Social Media as a Tool for Health- Related Topics	Mayteé Zambrano Núñez	2022	<ul> <li>process consisted of removing undesired data such as duplicate and corrupted information, hyperlinks, and foreign language text, if required.</li> <li>Various techniques such as linguistic inquiry and word count (LIWC), latent Dirichlet allocation (LDA), latent semantic analysis (LSA), nonnegative matrix factorization (NMF), word2vec, global vectors for word representation (GloVe), n-gram, principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), keyword filtering (KF), term frequency-inverse document frequency, and machine learning techniques were used for aspect extraction.</li> <li>Due to their non-contextual nature, lexicon-basedapproaches demonstrate reduced robustness in the presence of sarcasm or nuanced language. They rely solely on the sentiment of individual words, which may not capture the full context of the text.</li> </ul>

5	On Modelling for Bias-Aware Sentiment Analysis and Its Impact in Twitter	Ahsan Mahmood1, Hikmat Ullah Khan2 and Muhammad Ramzan	2020	<ul> <li>The statistical model proposed for identifying biased users and social bots in Twitter uses a simple solution to identify biased users. It calculates the biased percentage of a user's tweets using the formula BTuj = n/N</li> <li>The statistical model is used to identify biased users and social bots in Twitter.</li> <li>The statistical model itself may introduce biases in the identification process, potentially leading to skewed results.</li> <li>improve prediction outcomes, and contribute to a deeper understanding of user behavior on social media platforms</li> </ul>
6	Automatic Sentiment Annotation of Idiomatic Expressions for Sentiment Analysis Task	Bashar M. A. Tahayna, Ramesh Kumar Ayyasamy, and Rehan Akbar	2022	<ul> <li>augmentation technique using the idiom expansion method</li> <li>the methodology employed the BERT embedding model for the expansion approach</li> <li>The expansion procedure enhances the effectiveness of word disambiguation for sentiment analysis</li> <li>The automated idiom enrichment and annotation were shown to be beneficial for the performance of the sentiment classifier.</li> </ul>
7	Social Network and Sentiment Analysis: Investigation of Students Perspectives on Lecture Recording	Larian M. Nkomo, Ifeanyi G. Ndukwe, and Ben Kei Daniel	2020	<ul> <li>The study on the value of lecture recordings to student learning utilized social network and sentiment analysis techniques. These methods were chosen because they are useful in examining semi-structured and unstructured social media data</li> <li>These methods are useful in examining semi-structured and unstructured social media data, providing insights from individual messages</li> <li>The use of pre-trained classifiers in sentiment analysis can be disadvantageous as the context of the text is not always fully considered, potentially leading to misinterpretations.</li> </ul>

8	Improving Sentiment Analysis in Social Media by Handling Lengthened Words	Ashima Kukkar, Rajni Mohana, Aman Sharma, Anand Nayyar, and Mohd. Asif Shah	2023	<ul> <li>used a lexicon-based approach to improve sentiment analysis in social media</li> <li>ML approaches used for sentiment analysis include Random Forest (RF), Decision Tree (DT), Bayesian Network (BN), Logistic Regression (LR), Support Vector Machine (SVM), Maximum Entropy (ME), Ensemble Learning (EL)</li> </ul>
9	Distantly Supervised Lifelong Learning for Large-Scale Social Media Sentiment Analysis	Rui Xia, Jie Jiang, and Huihui He	2017	<ul> <li>introduces the concept of lifelong sentiment learning, which involves continuously learning from a stream of tasks and updating knowledge to adapt to new tasks. It describes the lifelong learning process, Lifelong Bagging model, and Lifelong Stacking model</li> <li>Most of the current statistical learning algorithms, such as logistic regression, na€ive Bayes, SVM, maximum entropy as well as the deep neural networks, are normally learned based on an isolated dataset and a single task</li> <li>The method relies on distant supervision information in social media texts, making it cheaply applicable to new domains without the need for manually labeled data.</li> </ul>
10	Aspect-level Sentiment Analysis for Social Media Data in the Political Domain using Hierarchical Attention and Position Embedding	Renny Pradina Kusumawardan i	2020	<ul> <li>the use of hierarchical attention-based position aware network (HAPN) model for data analysis. It also experiments with various architectures such as RNN and LSTM</li> <li>Aspect-level Sentiment Analysis for Social Media Data in the Political Domain using Hierarchical Attention and Position Embeddings</li> <li>LSTM,GRU,SimpleRNN,Adamoptimize r, Adadelta optimizer,SGD optimizer,RMSprop optimizer.</li> </ul>