# CHAPTER- 2

# LITERATURE REVIEW

*The literature overview of previous research on text sentiment analysis and ML and DL classification is presented in Chapter 2. This covers background information, related studies, and unmet research needs.*

## Background

Sentiment analysis has been a major area of research in ML, DL, and NLP in recent years because of its many academic and corporate uses as well as the quick development of Web 2.0 (Kanwal *et al.*, 2023). In this day and age, when the WWW is overloaded with text data, sentiment analysis of scientific citations is a highly debated and fascinating issue. After being analysed according to criteria, this data provides a wealth of vital information. The goal of sentiment analysis, often called opinion mining, is to extract the text's expressed attitudes, sentiments, views, emotions, and feelings—both positive and negative, as well as neutral (Raza *et al.*, 2019).

Trend analysis and opinion mining are other names for text sentiment analysis. To put it briefly, it is the act of assessing, digesting, evoking, and drawing conclusions from emotions in subjective literature. It is widely used in consumer choice research, stock and movie box office forecasts, and public opinion monitoring (Li, Jin and Quan, 2020). Sentiment classification is also called as polarity classification. It classifies the text is positive or negative in the sentence or documents. The sentiment analysis words are classified on the basis of semantic orientation that normally identifies the text weight, polarity, and strength. It is helpful to determine the marketing reviews and compile reviews, etc. The focus of aspect identification for sentiment analysis is determined by the accomplishment of sentiment orientation and opinion word detection. It falls into one of two categories: supervised or unsupervised. The unsupervised classification is the aspect detection in an unlabeled dataset and the supervised method is classify the aspect detection technique in a training dataset (T. Nikil Prakash1, 2020).

A key focus of NLP and AI studies is sentiment analysis, often called opinion mining. This field aims at extracting opinions in form of Subjectivity from text documents most probably used to deduce the attitude of individuals or groups. The exponential increase in online social networks and other such portals has further added to the requirement to make correct sentiment analysis models available for use to overcome the sheer overload of data being generated. The generic techniques of SA involving hand-crafted rule and lexicon based methods have been more and more complemented with more complex and accurate ML and DL methods recently (Singh3, 2024). The study of how computers and humans communicate via language is known as "Language Processing" (LP). An area of NLP called SA and opinion mining focuses on the exploration and analysis of opinion-bearing text descriptions of people’s feelings such as their sentiments, opinions, assessment, attitudes and even emotions. All of the data, web, and text mining relies on it and this particular area is currently one of the most vibrant in NLP (Nahar *et al.*, 2020).

## Related Work

This section discusses and analyses prior publications that were related to text sentiment analysis utilising DL and ML methods. key emphasis is on identifying a number of various methodological approaches, models or methodologies that have been used to analyse sentiments.

### Students’ Adaptability using Machine learning

In this study (Sampedro, 2024), was designed to provide a system that can use sentiment analysis to rate obtained movie reviews from IMDB to help the viewers decide on which particular movies are relevant to their tastes. Sentiment analysis (SA) simplifies the process of opinion summarization by extracting the sentiments the reviewer conveys. The algorithms employed for accuracy rate classification include the LR model, Linear SVM, and Multinomial NB. The study yielded a precision rate of 0.91 from the analysis of 6,157 data evaluations, suggesting a substantial presence of negative resistance. A data splitting technique was employed, where 25% of the dataset comprising 12,500 reviews was allocated for training purposes. The level of accuracy attained was 90.288%.

This research done by (Changala *et al.*, 2024), proposed to optimise sentiment analysis using three cutting-edge machine learning classifiers, SVM and Oner. Two benchmark datasets are used in the studies; one dataset is derived from Amazon, while the other is derived from IMDB movie reviews. they compare and analyze the results of these classification methods. The Naive Bayes learned rather quickly, but Oner shows more promise with a precision of 92.6%, an F-measure of 96%, and a properly categorized occurrence rate of 93.4%.

In this research (Singh3, 2024), offered an extensive overview of sentiment analysis as it pertains to AI and LLMs. An essential part of NLP, sentiment analysis has progressed greatly from simpler rule-based approaches to more complex DL systems. The paper traced the evolution of sentiment analysis over time, focussing on how the field has progressed from methods that relied on lexicons and patterns to those that use AI and deep learning. Handling multilingual messages, recognising sarcasm, and correcting biases are some of the key problems that are explored. The report analyses developing trends, reviews state-of-the-art methodologies, and lays out future research priorities to progress the subject. This research aims to get a thorough grasp of sentiment analysis within the framework of AI and LLM by integrating current methods and exploring possible future directions.

In this research (Zhan *et al.*, 2024), investigated methods for optimising sentiment analysis using big pre-trained language models like GPT-3 to enhance the impact and performance of the models and push NLP development forward. This paper introduces GPT-3 and Fine-tuning approaches, discusses their uses in sentiment analysis, and explains the significance of sentiment analysis as well as the limits of standard methods. Experimental findings demonstrate that the GPT-3 model may be fine-tuned using the fine-tuning approach, leading to high performance in the sentiment analysis task. If future sentiment analyses use large-scale language models, this work will serve as a valuable reference.

In this study done by (Zakaria and Sunyoto, 2023), performed a case study analysing review sentiment using the IMDB dataset. In their proposal, they used a Majority Voting method to combine LR with MNB, two powerful classification algorithms. Their Majority Voting solution takes into account the choices made by MNB and LR and uses the feeling that comes up most often as a final result. The purpose of merging the two approaches is to make sentiment analysis more effective. They evaluated the approach using an 80% training set and a 20% test set extracted from the IMDB dataset. Precision, accuracy, and recall were some of the performance indicators included in the evaluation. The experimental results showed that merging MNB and LR using Majority Voting greatly enhanced the performance of sentiment analysis. As compared to using each approach alone, the attained accuracy was 0.89% greater.

In this study (Jones, Omar and Mohammed, 2023), deployed an approach to generating targeted text-domain adversarial examples from inputs by leveraging the GPT-2 model. To build adversarial instances that potentially deceive sentiment analysis machines, their technique employed an iterative algorithm to produce perturbations of input textual samples. To validate their method, they apply it to Yelp, MR, and IMDB – three of the standard sentiment analysis datasets. An outcome shows that their method is capable of producing hostile cases that considerably diminish sentiment analysis algorithms' performance. On the Yelp, MR, and IMDB datasets, respectively, a reduction in accuracy of up to 67.3%, 68.1%, and 52.5% was attained. Additionally, they talk about the shortcomings of their methodology and the unresolved issues in this area. Ultimately, their research proves that GPT-2 can be a powerful adversarial example generator for NLP applications.

In this research done by (Tetteh and Thushara, 2023), investigated the sentiment towards films by use of a number of sentiment analysis tools based on dictionaries, including Text blob NB Analyser, VADER Sentiment Intensity Analyser, SpaCy, and Text blob. This study has revealed that out of all the methods explored, Text blob’s NB Analyser gives the best projected sentiment ratings and therefore, it is the best method. In case of IMDB movie reviews the suggested model has F1-score of 0.78 and accuracy score of 73%.

In the study (Mouthami *et al.*, 2023), The suggested model considers two different sets of data – multiclass and binary set of data. For the binary classification task, TS-GRU was applied, whereas for the multiclass tasks, they employed the Bi-LSTM. Pre-processing employed a number of classifiers, including bag of words and intra-word non-ordered perceptron skip-gram word2vec. For LSTM s symmetric Bi LSTM was used instead, because training a regular LSTM would entail a high computing cost. Though the Bi-LSTM significantly reduces computing costs, it produces a level of accuracy similar to the LSTM. With the use of sentiment analysis, they can see how people really feel about certain movies. Sentiment analysis is a subfield of NLP that aims to accomplish this goal by studying user writing and extracting meaning from it based on word arrangement and use. With the advent of new ML techniques, this research examines the performance of bidirectional LSTMs with different kernel sizes, both single- and multi-branch, on the IMDb dataset and using the Keras API. GRU attained an accuracy of 98.24%, while bi-LSTM reached 98.65%.

In this work done by (Kanwal *et al.*, 2023), developed a model that combined features of LSTM and Stacked Auto-encoder (SAE). The purpose of using SAE is to extract useful informational characteristics. LSTM was used to do further sentiment categorisation using the characteristics that were retrieved. An evaluation of the suggested model is carried out by dividing the IMDB dataset into five training/testing ratios. Quantitative measures include F1 score, sensitivity, specificity, recall, precision, and accuracy in classification. With an accuracy rate of 87% for sentiment classification, the hybrid findings worked optimally at a 90/10 ratio. The suggested hybrid model outperforms the industry standard models in terms of accuracy, including RNN, CNN, LSTM, NB, SVM, and GRU.

In this study (Dina, Ravana and Idris, 2022), IMDB, Yelp, and Amazon were subjected to hybrid feature selection utilising TF-IDF and SVM-RFE. Sentiment characteristics are chosen using the TF-IDF and then refined using SVM-RFE. Finally, a sentiment's positivity or negativity is determined using SVM. In two datasets, this work achieves better accuracy rates than the current techniques: 88% on the IMDB dataset and 84.5% on the Yelp dataset. With an accuracy of only 81.5%, the Amazon dataset falls short of the standards established by previous research.

In this research (Mohd Nafis and Awang, 2021), suggested a better hybrid feature selection method to boost ML-based sentiment categorisation. Acquiring and preparing the Sentiment Labelled and large IMDB customer review databases is the first milestone. The proposed feature selection approach, a hybrid of SVM and TF-IDF, is then tested on these two datasets. TF-IDF sets out to quantify the significance of characteristics. Feature evaluation and ranking are iterative processes in the SVM-RFE. The sentiment categorisation process will just use the top features derived from the ranking features. Then, to evaluate the suggested method, the SVM classifier is used. There are four metrics utilized to evaluate performance: recall, precision, accuracy, and F-measure. An experimental finding demonstrates encouraging performance, with measurement accuracy ranging from 84.54% to 89.56%, particularly when applied to the massive IMDB dataset. Results also outperformed competing approaches on certain datasets. As a result, a number of characteristics that need to be categorised decreased from 19.25% to 70.5% using the suggested method.

In this study (Xia, Ding and Liu, 2020), The use of bidirectional LSTM allows for more accurate identification of emotional polarity in brief texts by separately encoding the input sequence's context semantic information in order to get deeper emotional properties. The strategy's efficacy was verified using the publicly available Twitter dataset and the ACL movie review dataset. The model validates its good performance in datasets from multiple areas, as experimental results demonstrate that it obtains 66.45% accuracy on the Twitter dataset, 79.48% accuracy on the movie reviews dataset, and 90.34% accuracy on the IMDB dataset.

In this study (Hameed and Garcia-Zapirain, 2020), For BiLSTM with only one layer and utilizing the global pooling approach, the accuracy achieved was 80% achieved for MR, 85.780% on SST2, and 90.585% on IMDb. Having completed the analysis of the performance measures of their proposed method with that of the architectures of other models available in the literature, they concluded that their approach is relatively efficient. Therefore, the proposed architecture with the single layer of BiLSTMs is computationally light and can be thus used in sentiment analysis in real-time.

In this research (Dai, Chen and Li, 2019), used a data poisoning attack as a backdoor against text categorisation using LSTM. After injecting this backdoor, the model will label all the text samples containing some specific trigger phrase chosen by the adversary to the specific category of the former’s choice. The backdoor attack is undetectable, and the model's performance is unaffected by the injection of the backdoor. In a black-box environment, where the attacker is unaware of the model structures and training methods other than a limited quantity of training data, they contemplate a backdoor attack. They validate the assault by conducting a sentiment analysis experiment on the IMDB movie review dataset. Their assault has a 1% poisoning rate and a 96% success rate, according to the experiments.

In this study (Sajeevan and Lakshmi, 2019), used a mix of LSTM and CNN deep learning algorithms to analyse MOVIE reviews. Feature learning is one area where CNN shines as a popular deep learning approach. For long-term adaptation, there is a special kind of RNN called LSTM. Information may be retained for a far longer duration using this strategy. They use two distinct DL models to sort IMDB reviews of movies. The first model is LSTM-CNN integrated whereas the second one follows a CNN-LSTM integrated model. The researchers found that, when comparing the two models, the LSTM-CNN model outperformed the CNN-LSTM model with an overall accuracy of 79%.

### Students’ Adaptability using Deep learning

In this research (Shabbir and Majid, 2024), utilized a framework based on DL techniques for sentiment analysis of Urdu language is presented that comprises data curation, pre-processing, and classification stages. A dataset of translated Urdu movie reviews from IMDB, which is freely accessible, has been used. They conducted experiments on sentiment classification using three different deep learning models: 1D-CNN, LSTM, and Multilingual-MiniLM-L12-H384 transformer. The findings showed that the proposed transformer approach had a remarkable accuracy of 89.36% when used for the Urdu language.

This work done by (Saad *et al.*, 2024), proposed a full deep-learning framework that avoids some of the disadvantages related to sequential frameworks while integrating the advantages that regards both the Transformer as well as sequence models. This architecture uses the IMDB dataset of 50K movie reviews to analyze the reviewers' expressions and the proposed model has been experimented with three advanced transformer-based deep-learning approaches such as BERT, Roberta, and Distil BERT. Of these, the Robustly optimized BERT approach (RoBERTa) fares better than the other two, obtaining an accuracy of 95.02 %, which is higher than 94.12% of BERT and 92.82% of Distil BERT approaches as well as the advance models.

In this study (Sultana *et al.*, 2024), represented the previous studies of emotional analysis and illustrates the methodology of their work. The methodology explains data extraction, data pre-processing, text pre-processing, feature extraction, feature selection, and so on. The dataset applied in the study is an IMDb movie reviews dataset containing equal amounts of samples for training and testing. Then, they discussed sentiment analysis techniques which are SNN, CNN, and RNN. Using a method, the outcome states that the simple neural network model generates an accuracy of 74.99% and a Convolutional Neural Network of 85.79%. Besides, the Recurrent Neural Network shows 86.46% which is the highest one. Furthermore, based on the results of the confusion matrix, they investigated the optimum model to attain the highest F1 score, recall, and precision.

In this study (Beniwal *et al.*, 2024), made use of DL algorithms in a unique hybrid way to analyse the sentiment of IMDB movie reviews. A proposed hybrid DL model, i.e. CNN + LSTM achieved an accuracy of 96.01%, which outperforms the results obtained via multiple deep learning models like logistic regression, pre-trained text blob model, and Convolutional Neural Network (CNN). Also, compared to the existing literature, the findings obtained by the proposed model are superior. A state of art used in this study explains and approaches sophisticated problems efficiently and effectively.

This study done by (Hasan and Shetty, 2024), implemented a new approach to sentiment analysis using a GAN architecture with LRNN on the IMDB movie review dataset. The main issues of the standard approaches and methods when applying them in training are instability and vanishing gradients. Their approach avoids these problems because it is based on the effectiveness and stability of the LRNN that improves the accuracy and reliability of the sentiment analysis. Efficiently synthesising and discriminating between produced sentiment-laden textual data and genuine data is the GAN framework's forte. It includes an LRNN-equipped discriminator and generator. The discriminator sorts real data from fake data and rates the sentiment correctness of the generated content while the generator works on producing authentic, sentiment-laden text. A gradient vanishing problem is a common issue in standard GAN models. Incorporating LRNN into the generator and discriminator resolves the issue. As a result, the training process becomes more stable and performance is enhanced. Their findings greatly enhance the accuracy of sentiment analysis, outperforming many popular models, with a 91.30% accuracy rate on the IMDB dataset.

This work done by (Mishra and Patil, 2023), used DNNs to categorise user-provided movie reviews based on their emotion. Popular DNNs utilised for sentiment analysis include CNNs and LSTMs. Data used for sentiment analysis comes from the Internet Movie Database (IMDb), which has fifty thousand reviews of movies. Both CNN and LSTM designs have their uses, and eventually, a mix of the two will be used. When comparing LSTM, CNN, and CNN-LSTM architectures using accuracy and loss criteria, LSTM architecture comes out on top. In descending order of accuracy, it find GRU (53%), CNN (85%), LSTM (87%), and CNN-LSTM (85%). The loss function makes use of the Adam optimiser and binary cross-entropy.

In this study (Mutinda, Mwangi and Okeyo, 2023), proposed the LeBERT model for sentiment classification, which combines the sentiment lexicon with N-grams, BERT, and CNN. The model begins by vectorising words taken from a subset of the input text using sentiment lexicon, N-grams, and BERT. CNNs are used as DNN classifiers to map features and compute sentiment classes as output. When evaluating the proposed method, they look at review data from three public sources: Amazon items, Imbed movies, and Yelp eateries. Accuracy, precision, and the F-measure are some of the metrics used to evaluate the model's performance. Experimental results show that the proposed LeBERT model outperforms the state-of-the-art models in binary sentiment classification with an F-measure score of 88.73%.

In this study (Sakthiyavathi and Saruladha, 2023), emphasised the use of textual data for emotion identification. An attention mechanism, doc2vec, CNN, and Bi-GRU are all part of the hybrid model that is introduced in this study. The first step of the proposed approach is to use a Doc2vec model to transform the text into vectors. First, the doc2vec model gathers the semantic data, and then the CNN model takes it in. The local characteristics are captured by the CNN model. To acquire these contextual characteristics, Bi-GRU, GRU, and Bi-LSTM work together. An attention mechanism and dropout regularisation are used to fine-tune the performance of the generated model. The IMDB and Emotions datasets, which are considered industry standards, were used to test the model. A multi-class classification accuracy of 82.84% was achieved using the suggested hybrid model.

In this research done by (Sen and Chaturvedi, 2023), made use of DL using the GRU architecture, the results were impressive, and the input text's underlying semantic meaning was often revealed. The GRU model seems to be much more effective, with a variable loss of 0.4728, a maximum accuracy of 97.20%, and a minimum loss of 0.0783.

This study completed by (Abdul Ameer *et al.*, 2023), offered a way to do sentiment analysis using a CNN with the IMDB dataset, employing GloVe and Word2Vec. The testing results showed that their CNN technique achieved an accuracy of 89.8 percent, which was higher than the then-gold standard models, GloVe and Word2Vec.

This study done by (Trueman *et al.*, 2022), recommended a BERT-based classification model for n-gram sentiment analysis. In particular, the massive IMDB movie review dataset is used, which includes fifty thousand examples. The dataset has been tokenised and encoded into several forms of shorthand notation, including unigrams, bigrams, trigrams, and combinations thereof. These retrieved characteristics were subjected to the suggested BERT model. The F1 score as well as its micro, macro, and weighted-average scores are then used to assess this model. For every n-gram feature, the model's performance is on par with the most advanced techniques. By way of example, the model outperforms other n-gram features when employing a mix of bigram and trigram features (94.64% accuracy), and when utilising unigram, bigram, and trigram features (94.68% accuracy).

In this research (Thinh *et al.*, 2019), evaluated the proposed sentiment analysis challenge for DL from the IMDb review sentiment dataset. The most important of them include convolutional layers, max pooling, and batch normalisation. The vanishing gradient issue is addressed by merging the input values with the retrieved features using a residual connection, which is then fed into a recurrent layer. 90.02% accuracy is achieved by their top model.

## Research Gap

Although recent years have seen great progress in sentiment analysis using ML and other DL models, there are still some research gaps. Current studies are actively searching for the best way to improve separate classifiers or use their connection to improve the performance on certain datasets such as IMDB. In general, while there is extensive work on the use of individual architectures such as CNN, LSTM, GRU, and transformer, how best to integrate them in a way that maximizes the accuracy, robustness and scalability of the model of interest is not well explored. Furthermore, despite fine performance of models such as BERT and RoBERTa certain issues remain unresolved, for instance, lack of the incorporation of explainable AI (XAI) investigation. There is also evidence of bias in sentiment classification that is not fully expounded. However, the general resilience of models to adversarial assaults, the viability of adversarial training in terms of speed for real-time implementations, and the real-world concerns of model deployment, including its versatility and stability, remain important research questions. Despite the promise shown by the use of different languages, such as Urdu in sentiment analysis, there is still very limited research on applying such models to different languages and cultures. Moreover, while recent work focuses on training stability and vanishing gradients, there is more to be explored and done concerning those issues in hybrid models as well as in the practical application of AI-driven sentiment analysis with the integration of large language models (LLMs) to fill the gap between conventional methods and advance AI methods.

# REFERENCES

Abdul Ameer, S.A. *et al.* (2023) ‘Hybrid Deep Neural Networks for Improved Sentiment Analysis in Social Media’, in *ICSCCC 2023 - 3rd International Conference on Secure Cyber Computing and Communications*. Available at: https://doi.org/10.1109/ICSCCC58608.2023.10176880.

Beniwal, R. *et al.* (2024) ‘A Hybrid Deep Learning Model for Sentiment Analysis of IMDB Movies Reviews’, in *2024 Asia Pacific Conference on Innovation in Technology (APCIT)*, pp. 1–7. Available at: https://doi.org/10.1109/APCIT62007.2024.10673659.

Changala, R. *et al.* (2024) ‘Sentiment Analysis Optimization Using Hybrid Machine Learning Techniques’, in *2024 Parul International Conference on Engineering and Technology (PICET)*, pp. 1–5. Available at: https://doi.org/10.1109/PICET60765.2024.10716161.

Dai, J., Chen, C. and Li, Y. (2019) ‘A backdoor attack against LSTM-based text classification systems’, *IEEE Access* [Preprint]. Available at: https://doi.org/10.1109/ACCESS.2019.2941376.

Dina, N.Z., Ravana, S.D. and Idris, N. (2022) ‘An Experimental Study on Hybrid Feature Selection Techniques for Sentiment Classification’, in *International Conference on Software, Knowledge Information, Industrial Management and Applications, SKIMA*. Available at: https://doi.org/10.1109/SKIMA57145.2022.10029452.

Hameed, Z. and Garcia-Zapirain, B. (2020) ‘Sentiment Classification Using a Single-Layered BiLSTM Model’, *IEEE Access* [Preprint]. Available at: https://doi.org/10.1109/ACCESS.2020.2988550.

Hasan, M. and Shetty, S. (2024) ‘Sentiment Analysis With Lipschitz Recurrent Neural Networks Based Generative Adversarial Networks’, in *2024 International Conference on Computing, Networking and Communications (ICNC)*, pp. 485–489. Available at: https://doi.org/10.1109/ICNC59896.2024.10555933.

Jones, R., Omar, M. and Mohammed, D. (2023) ‘Harnessing the Power of the GPT Model to Generate Adversarial Examples’, in *2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE)*, pp. 1699–1702. Available at: https://doi.org/10.1109/CSCE60160.2023.00279.

Kanwal, I. *et al.* (2023) ‘Sentiment Analysis Using Hybrid Model of Stacked Auto-Encoder-Based Feature Extraction and Long Short Term Memory-Based Classification Approach’, *IEEE Access* [Preprint]. Available at: https://doi.org/10.1109/ACCESS.2023.3313189.

Li, W., Jin, B. and Quan, Y. (2020) ‘Review of Research on Text Sentiment Analysis Based on Deep Learning’, *OALib* [Preprint]. Available at: https://doi.org/10.4236/oalib.1106174.

Mishra, M. and Patil, A. (2023) ‘Sentiment Prediction of IMDb Movie Reviews Using CNN-LSTM Approach’, in *2023 International Conference on Control, Communication and Computing, ICCC 2023*. Available at: https://doi.org/10.1109/ICCC57789.2023.10165155.

Mohd Nafis, N.S. and Awang, S. (2021) ‘An Enhanced Hybrid Feature Selection Technique Using Term Frequency-Inverse Document Frequency and Support Vector Machine-Recursive Feature Elimination for Sentiment Classification’, *IEEE Access* [Preprint]. Available at: https://doi.org/10.1109/ACCESS.2021.3069001.

Mouthami, K. *et al.* (2023) ‘Text Sentiment Analysis of Film Reviews Using Bi-LSTM and GRU’, in *2023 4th International Conference on Electronics and Sustainable Communication Systems, ICESC 2023 - Proceedings*. Available at: https://doi.org/10.1109/ICESC57686.2023.10193121.

Mutinda, J., Mwangi, W. and Okeyo, G. (2023) ‘Sentiment Analysis of Text Reviews Using Lexicon-Enhanced Bert Embedding (LeBERT) Model with Convolutional Neural Network’, *Applied Sciences (Switzerland)* [Preprint]. Available at: https://doi.org/10.3390/app13031445.

Nahar, K.M.O. *et al.* (2020) ‘Sentiment analysis and classification of arab jordanian facebook comments for jordanian telecom companies using lexicon-based approach and machine learning’, *Jordanian Journal of Computers and Information Technology* [Preprint]. Available at: https://doi.org/10.5455/jjcit.71-1586289399.

Raza, H. *et al.* (2019) ‘Scientific text sentiment analysis using machine learning techniques’, *International Journal of Advanced Computer Science and Applications* [Preprint]. Available at: https://doi.org/10.14569/ijacsa.2019.0101222.

Saad, T.B. *et al.* (2024) ‘A Novel Transformer Based Deep Learning Approach of Sentiment Analysis for Movie Reviews’, in *2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*, pp. 1228–1233. Available at: https://doi.org/10.1109/ICEEICT62016.2024.10534588.

Sajeevan, A. and Lakshmi, K.S. (2019) ‘An enhanced approach for movie review analysis using deep learning techniques’, in *Proceedings of the 4th International Conference on Communication and Electronics Systems, ICCES 2019*. Available at: https://doi.org/10.1109/ICCES45898.2019.9002043.

Sakthiyavathi, K. and Saruladha, K. (2023) ‘Design of Hybrid Deep Learning Model for Text-based Emotion Recognition’, in *2023 2nd International Conference on Advances in Computational Intelligence and Communication, ICACIC 2023*. Available at: https://doi.org/10.1109/ICACIC59454.2023.10435072.

Sampedro, G.A. (2024) ‘What’s Next?: Exploring Machine Learning-Based Approaches to Content Suggestions Using IMDb Movie Reviews’, in *2024 International Conference on Electronics, Information, and Communication (ICEIC)*, pp. 1–4. Available at: https://doi.org/10.1109/ICEIC61013.2024.10457130.

Sen, M. and Chaturvedi, K. (2023) ‘Sentiment Analysis of IMDB Movies Dataset Using Deep Learning Based GRU Model’, in *International Conference on Sustainable Communication Networks and Application, ICSCNA 2023 - Proceedings*. Available at: https://doi.org/10.1109/ICSCNA58489.2023.10370081.

Shabbir, M. and Majid, M. (2024) ‘Sentiment Analysis From Urdu Language-based Text using Deep Learning Techniques’, in *2024 5th International Conference on Advancements in Computational Sciences (ICACS)*, pp. 1–5. Available at: https://doi.org/10.1109/ICACS60934.2024.10473232.

Singh3, S.G.R.R.S.N. (2024) ‘Comprehensive Study on Sentiment Analysis: From Rule based to modern LLM based system’, pp. 1–16. Available at: https://doi.org/https://doi.org/10.48550/arXiv.2409.09989.

Sultana, A. *et al.* (2024) ‘Sentiment Analysis with Deep Learning Methods for Performance Assessment and Comparison’, in *2024 International Conference on Image Processing and Robotics (ICIPRoB)*, pp. 1–6. Available at: https://doi.org/10.1109/ICIPRoB62548.2024.10544219.

T. Nikil Prakash1 (2020) ‘A Comparative study of Lexicon based and Machine learning based Classifications in Sentiment analysis’, *International Journal of Data Mining Techniques and Applications*, 9(2), pp. 83–87. Available at: https://doi.org/10.20894/ijdmta.102.009.002.001.

Tetteh, M. and Thushara, M. (2023) ‘Sentiment Analysis Tools for Movie Review Evaluation - A Survey’, in *Proceedings of the 7th International Conference on Intelligent Computing and Control Systems, ICICCS 2023*. Available at: https://doi.org/10.1109/ICICCS56967.2023.10142834.

Thinh, N.K. *et al.* (2019) ‘Sentiment Analysis Using Residual Learning with Simplified CNN Extractor’, in *Proceedings - 2019 IEEE International Symposium on Multimedia, ISM 2019*. Available at: https://doi.org/10.1109/ISM46123.2019.00075.

Trueman, T.E. *et al.* (2022) ‘An N-gram-Based BERT model for Sentiment Classification Using Movie Reviews’, in *International Conference on Artificial Intelligence and Data Engineering, AIDE 2022*. Available at: https://doi.org/10.1109/AIDE57180.2022.10060044.

Xia, H., Ding, C. and Liu, Y. (2020) ‘Sentiment analysis model based on self-attention and character-level embedding’, *IEEE Access* [Preprint]. Available at: https://doi.org/10.1109/ACCESS.2020.3029694.

Zakaria and Sunyoto, A. (2023) ‘Hybrid Sentiment Analysis: Majority Voting with Multinomial Naive Bayes and Logistic Regression on IMDB Dataset’, in *2023 6th International Conference on Information and Communications Technology, ICOIACT 2023*. Available at: https://doi.org/10.1109/ICOIACT59844.2023.10455937.

Zhan, T. *et al.* (2024) ‘Optimization techniques for sentiment analysis based on LLM (GPT-3)’, *Applied and Computational Engineering*, 67(1), pp. 27–33. Available at: https://doi.org/10.54254/2755-2721/67/2024ma0060.