A Review: Effective Machine Learning Algorithms for Text-Based Emotion Detection

Bindu K[1], Dr. Manjunatha R C[2]
[1]Research Scholar, Global Academy of Technology, Bangalore, India
[2]Professor, Department of ECE, Global Academy of Technology Bangalore, India

Abstract—**Emotion identification from text is a specialist field of natural language processing (NLP). Emotion detection is usually used to identify human feelings like joy, anger, fear, sadness, disgust, or surprise, whereas sentiment analysis generally classifies text as positive, negative, or neutral. Text-based emotion plays an important role in the field of Natural Language Processing (NLP), which shows the discrimination of emotional states formulated in the text. As there is a tremendous increase in user-generated data across digital platforms, emotion detection has become more significant in various fields including mental health evaluation, customer feedback interpretation, and social media surveillance. This manuscript investigates the effectiveness of diverse machine learning algorithms in the identification of emotions from textual data. It conducts a comparative analysis of traditional methodologies such as Naïve Bayes, Support Vector Machines and Decision Trees along with more sophisticated approaches that encompass deep learning techniques like Recurrent Neural Networks, Long Short-Term Memory and Transformer-based Networks. The research underscores the advantages and drawbacks of these algorithms while highlighting the necessity of selecting contextually appropriate models to enhance emotion recognition. Understanding emotions expressed in written language enables deeper insights into user behaviour, opinion, and intent. This is especially helpful in fields like social media analysis, customer service, mental health monitoring, and human-computer interaction.**

Index Terms—**Emotion Detection, Machine Learning, Natural Language Processing, Navie Bayes, Support Vector Machine**

I. INTRODUCTION

Machine Learning (ML) and Artificial Intelligence (AI) models are very effective in solving challenging issues.

Natural language processing (NLP) represents a specialized domain within ML that focuses on the generation and interpretation of human language. NLP has achieved significant success in this field. As there are ambiguities in NLP, level of complexity becomes extremely challenging [1]. NLP includes classification, information extraction, similarity matching, summarization and so on.

The classification subdomain consists of a diverse array of tasks, such as sentiment analysis [2], emotion classification [3],[4],[5], fake news detection [6],[7] as well as bot and gender identification [12], and hate speech detection [13], among others. Even though sentimental analysis and emotion detection are used together but they differ profoundly. Sentimental Analysis tells whether it is positive, neutral, negative whereas emotion detection helps to find in-depth emotions like sadness, anger, happy etc.

Emotion detection from textual data has become a rapidly evolving area within the broader discipline of natural language processing (NLP), aimed at detecting and categorizing the emotional undertones encapsulated within written communication. As human interactions have gradually shifted towards digital platforms such as social media, conversational agents, and customer support engagements, it's become very important to understand then underlying information for a few applications, such as, mental health evaluation, and facilitating communication between humans and computers. Due to the inherent subjectivity and ambiguity of language, as well as the lack of contextual and nonverbal indications that usually go along with emotional expressions in spoken or in-person interactions, this process has lot of difficulties.

Recent developments in machine learning and deep learning approaches which use techniques like Recurrent Neural Networks (RNNs), transformer

architectures, and language models that have already been trained, such as BERT has led to the development of emotion detection. However, achieving high performance is dependent on domain specific complexities, and the capability to interpret sarcasm, common expressions, and cultural distinctions within linguistic concepts. This study aims to examine and assess methodologies for the effective detection of emotions within textual content, emphazing on accuracy, generalizability and applicability across various platforms such as Facebook, Instagram, and Twitter where individuals consistently articulate their sentiments regarding numerous topics, issues and grievances, and share their perceptions concerning everyday phenomena.

II. EMOTION MODELS

Emotion is a term within the English lexicon that signifies a perturbation of a physiological character. Historically, prior to the 19th century, constructs such as desire, hunger, and love were perceived as cognitive phenomena. Nevertheless, during the 19th century, there was a paradigm shift wherein emotions began to be reconceptualized as a psychological construct. In the discipline of psychology, intricate affective states that affect an individual's actions, cognition, and conduct are referred to as emotions [21]. The models of emotion can be systematically categorized into following:

1) Dimension-Based Emotional Model: This model characterizes emotions according to dimensions such as valence, provocation, and power. Valence denotes the polarity inherent in the emotion, provocation relates to the intensity of the affective experience, while power signifies the extent of control exercised over the emotional state [22]. The psychological states arising from these dimensions are depicted in Figure. 1.

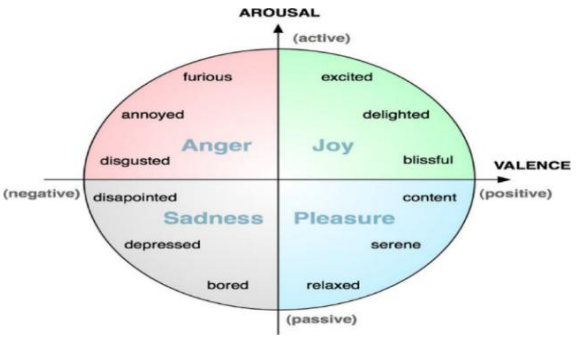


Figure1: Two-Dimensional Emotional Model

2) Plutchik's Wheel of Emotion: The two-dimensional model depicted in Figure. 2 illustrates Plutchik's wheel of emotion [23], which encapsulates emotions within a circular schema. The wheel is structured into concentric circles, with the innermost circle representing a collection of eight fundamental emotions: anxiety, surprise, rage, happiness, faith, anger, nervousness, despair, and disgust. Furthermore, these eight primary emotions constitute the outermost layer of the wheel and can be synthesized with primary emotions.

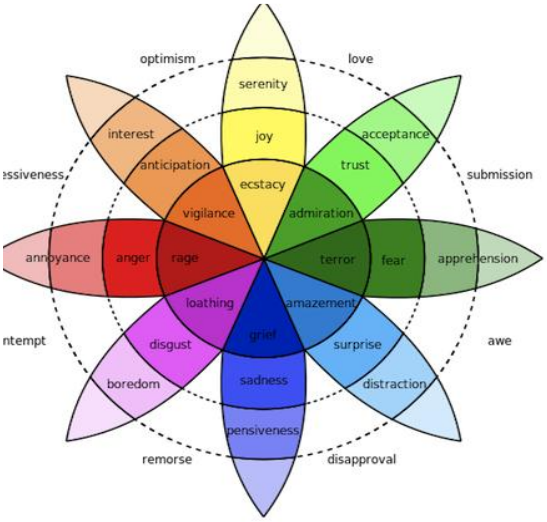


Figure 2: Plutchik's Wheel of Emotions depicting two dimensional

3) Categorical Emotion Model: This model distinctly categorizes emotions into anger, joy, fear, and sadness. It is based on specific classifications that encompass four, six, and eight emotional categories. The four refer to the primary emotional states: positive, negative, relaxed, and exciting. Simultaneously, the six models encompass happiness, fear, surprise, anger, sadness, and disgust (commonly referred to as Paul Ekman's emotion model). The eight emotional constructs include anxiety, surprise, rage, happiness, faith, anger, nervousness, despair, and disgust (commonly recognized as Plutchik's emotion model). Among these theoretical frameworks, a considerable number of researchers have employed the models posited by Ekman and Plutchik [24], while alternative models consist of those proposed by Izard [25], [26], Shaver Emotion Model [27], and Tomkins [28]. Figure 3 elucidates these emotion models.

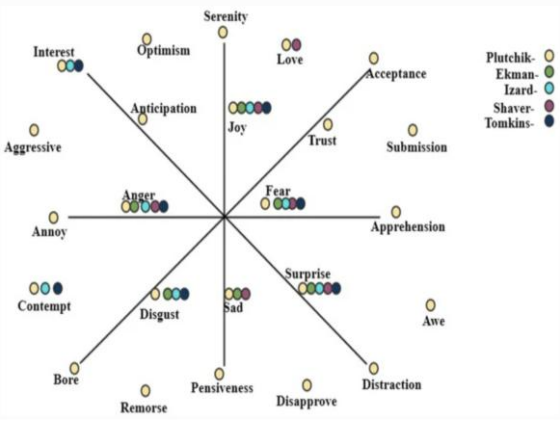


Figure 3: Image of different categorical emotion model

III. APPROACHES FOR EMOTION DETECTION

Numerous methodologies are employed for the detection of emotions from textual data, encompassing lexicon-based, machine learning (ML), deep learning, and hybrid methodologies.

A. Lexicon-Based Emotion Detection Methodologies:
These methodologies are predicated on predefined dictionaries of terms that are associated with specific emotional states.

Emotion Lexicons: To assign emotions based on the existence of particular words, use tools like WordNet-Affect, EmoLex, or the NRC Emotion Lexicon.

Rule-Based Systems: Implement heuristic principles to identify emotions derived from word combinations, intensity modifiers (e.g., “very,” “slightly”), and negation constructs.

The Word-Net-Affect represents an augmented version of WordNet, comprising a compendium of words accompanied by their respective emotional labels. Concurrently, the NRC Lexicon encompasses a collection of 14,000 words, each associated with distinct emotions and sentiments. These lexicons categorize words according to their associated emotional states. Nonetheless, a critical limitation of this classification system is its disregard for the degree of emotion's focus or intensity. It excludes additional variables that indicate the intensity of emotions and just measures the level of feelings. As a result, these lexicons are less effective. In order to solve this, Li et al. [31] put out a robust model for forecasting the word-level emotion distribution that may assign emotions with intensity and improve the lexicon's informativeness by including the NRC-valence arousal dominance dimensional dictionary. Braun and colleagues [32] presented an Emotional Football Corpus (MEmoFC) which encompasses football-related data derived from English and German online sources. This corpus is comprised of two distinct metadata tables: one detailing match particulars and the other enumerating football abbreviations. Both tables are instrumental in referencing the results of football matches as well as the articulation of both positive and negative sentiments. The authors further clarify that this corpus can be utilized across various research methodologies to influence the outcomes of games.

B. Machine Learning-Based Emotion Detection Approaches

Supervised learning and deep learning techniques are the main components of machine learning-based techniques for textual emotion identification. Supervised learning trains models such as Naive Bayes, Support Vector Machines, or Logistic Regression using labeled datasets. In contrast, deep learning uses neural networks—including CNNs and RNNs like LSTMs and GRUs—to automatically extract patterns and features from textual input. Additionally, hybrid approaches combining both classical machine learning and deep learning techniques are also employed for improved accuracy.

I. Supervised Learning Approaches:

1.Naive Bayes:Bayes' theorem is used by a probabilistic classifier to forecast the likelihood that a text will fall into a specific emotion category.

2.Support Vector Machines (SVM):
SVMs determine which hyperplane is best for dividing data points into distinct emotion groups.

3.Logistic Regression:
A statistical model that forecasts the likelihood that a text will be associated with a particular emotion using logistic function.

4.Decision Trees:
Decision trees classify text based on a series of decisions represented as a tree-like structure.

Hasan et al. [34] employed machine learning techniques, specifically Naïve Bayes, decision tree, and support vector machine (SVM), for the purpose of emotion recognition in textual data. The approach was

segmented into two main phases: First, a dataset was aggregated from Twitter utilizing hashtags, followed by the model training process. In the following stage, a dual-layered EmoText Stream was established to filter out emotionless tweets and to discern emotions using the trained model developed previously. The SVM algorithm attained a precision rate of 90% in the identification of emotions. The logistic regression (LR) model demonstrated a recall rate of 83% among all classifiers employed. Wikarsa et al. [42] implemented natural processing methods for the detection of emotions from Twitter data via Naïve Bayes techniques. They extracted 100 tweets utilizing the Twitter API, followed by preprocessing steps that included the removal of stop words, URLs, and the transformation of emotions into textual representations. The emotions were classified into emotions like happiness, sorrow, fear, disgust, surprise, and rage. To evaluate the performance of the classifier, they used 10-fold cross-validation, with the accuracy of the model for the Naive Bayes classifier reaching 83%. Mashal et al. [45] put forth a model that may identify subtle differences in the level of intensity of emotions. 30 references provided the data, which was then pre-processed by adding 70 references. A vector of features was created with the intention of predicting four different emotional states: fear, anger, sadness, and happiness. To predict the level of emotion, the linear regression approach was employed; however, it faced limitations regarding the restricted number of categories available for forecast. Using emotion corpora, Nida et al. [46] designed an automatic emotion classifier for Twitter. They each took characteristics out of the dataset and used to find synonyms for emotions using the WordNet emotion dictionary. Their study revealed the contextual meaning of words as well as interdependence within phrases. They achieved accuracy rates of 60%, 63%, and 67.86% for three of the six Ekman categories of emotions that they used to train the SVM classifier. different corpora of emotions that were examined.

Five machine learning techniques for sentiment analysis have been assessed by S. Indhumathi and F. Mary Harin Fernandez [1]: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), Logistic Regression (LR), and Naive Bayes (NB). On the Twitter dataset, SVM attains the highest accuracy of 91.02%, but Logistic Regression excels on the IMDB dataset with an accuracy of 87.39%. On Twitter, Naive Bayes exhibits good precision but poor recall.Random Forest maintains balanced performance, whereas KNN underperforms, especially on the IMDB dataset with 71.08% accuracy.J. López, Abraham Sánchez López et al.,[2] have used effective machine learning algorithms for sentiment analysis, as highlighted in the paper, include Support Vector Machine (SVM), Random Forest, and Ridge Classifier. These supervised algorithms have demonstrated superior performance, achieving accuracy values exceeding 80% on the dataset of tweets related to artificial intelligence. The Random Forest algorithm is noted for its ensemble strategy, which aggregates predictions from multiple decision trees, enhancing its classification capabilities in sentiment analysis task.

II. Deep Learning Approaches:

1.Recurrent Neural Networks (RNNs):

RNNs, including LSTMs and GRUs, are well-suited for processing sequential data like text. They can capture long-range dependencies between words and emotions.

2.Convolutional Neural Networks (CNNs):

CNNs can be used to extract features from text by scanning through the input sequence, capturing local patterns and relationships between words.

3.Transformers:

More advanced architectures like transformers (used in models like BERT) have gained popularity for their ability to understand context and nuances in text, leading to improved emotion detection accuracy.

4.Hybrid Approaches:

Integrating various deep learning models, such as CNNs and LSTMs, can capitalize on the advantages of each architecture to enhance performance.

A. Ramana Venkata [63] the study focuses on a Nonlinear Deep Learning Framework for sentiment analysis which includes an attention mechanism, Convolutional Neural Networks (CNN), Bidirectional LSTM (BiLSTM), and BERT embeddings. These elements improve classification accuracy as they effectively capture intricate sentiment patterns. The paper highlights the advantages of its hybrid method over conventional techniques, eliminating sentiment

identification issues and enhancing performance metrics including precision, recall, precision, and F1-score, even though it does not specifically name various other algorithms.

The CNN-LSTM-based deep learning model was implemented by Abdullah et al. [48] to identify emotions in Arabic tweets. Two distinct sets of trials were used by them: The CNNLSTM model was employed in experiment 2, while the feed-forward network was used in experiment 1. In experiment 1, the researchers employ three hidden layers and fully interconnected layers to feed their model with 4900 input vectors. In contrast, 300 vectors were fed into the CNN model in experiment 2. For experiment 1, the model's accuracy was 40%, while for experiment 2, it was 605. The issue is that systems were used on a very tiny dataset, even if the models reached an adequate level of accuracy. To extract emotions from text data, Huang et al. [49] employed a 4-part Episodal Memory Network (EMN) in conjunction with a self-attention model to identify the emotions from text data. Anger, fear, joy, and sorrow are the four fundamental emotions to which they employed the SemEval dataset. The EMN has outperformed the CNN, LSTM, and RNN models in terms of accuracy. The model's F1 score was 64.3%, recall was 63.1%, and precision was 56.8%. Although there were only a few categories, the model proved effective in identifying emotions.

B. A model for emotion detection that combined the Bi-LSTM, Self-Attention, and Convolution Neural Network (CNN) was presented by Polignano et al. [50]. They discovered that the most effective method for enhancing text-based emotion recognition performance is word embedding. Thus, Google Word Embedding, GloVe Embedding, and FastText Embedding were the three embedding systems they compared the ISEAR, SemEval-2018, and SemEval-2019 datasets were utilized. The outcomes demonstrated the high recall value, accuracy, and performance of ISEAR. Joy, guilt, rage, fear, shame, and disgust are among the emotion classes available in GloVe embedding and FastText. Conversely, FastText embedding improves precision, recall, and F1 measure in SemEval-2018 and 2019. They concluded that FastText is a great embedding approach for further study. Deep learning has been applied to text data sentiment analysis by Dianqing Bao and Wen-Hao Su [5].

C. Challenges and Limitations

Despite rapid advancements, significant hurdles persist:

1.Ambiguity and Sarcasm: Sarcastic statements often flip emotional meaning, challenging even sophisticated models (Rajadesingan et al., 2015).

2.Data Imbalance: Datasets typically overrepresent emotions like happiness and anger while underrepresenting subtler emotions like trust or anticipation.

3.Interpretability: Black-box nature of deep learning models raises concerns over trust and explainability, particularly in sensitive domains (Doshi-Velez & Kim, 2017).

D. Future Directions

Emerging trends point toward:

1.Explainable AI (XAI): Designing interpretable models that can justify their emotional classifications (Samek et al., 2017).

2.Commonsense Reasoning Integration: Enhancing emotion recognition by embedding knowledge graphs like ATOMIC or COMET (Sap et al., 2019).

3.Cross-lingual Emotion Detection: Developing models that generalize emotions across languages and cultures without extensive labeled data.

IV. CONCLUSION

This review offers substantial insights into the methodologies of textual emotion detection and elucidates the prevailing techniques and evaluative criteria employed in the identification of emotional content within textual data. The investigation underscored the various challenges and limitations that permeate the existing literature pertaining to tasks associated with emotion detection. Additionally, it offered workable solutions to these problems in order to improve the effectiveness of emotion detection systems. In the end, the study claimed that deep learning and machine learning paradigms have greatly improved accuracy in comparison to traditional rule-based methodologies.

Table 1: Studies on Emotion Detection

Author	Objective	Results	Limitation
S Indhumathi, F. Mary Harin Fernandez	They have considered machine learning algorithms like Logistic Regression and Naive Bayes Support Vector Machine K-Nearest Neighbors, Random Forest.	The study found that the highest accuracy of 91.02% was achieved by SVM method on the Twitter dataset, while Logistic Regression performed best on the IMDB dataset with an accuracy of 87.39%.	The study highlights that K-Nearest Neighbors (KNN) underperforms, particularly in handling the complexities of the IMDB dataset, achieving a lower accuracy of 71.08%. Naive Bayes, while demonstrating high precision on the Twitter dataset, has a relatively lower recall score.
J.Lopez, Abraham Sanchez Lopez et al.,	The research aims to evaluate a set of supervised machine learning algorithms for sentiment analysis, focusing on various strategies and types of algorithms, including distance-based methods, ensemble techniques, and advanced algorithms like perceptron and Ridge Classifier.	Random Forest, Ridge Classifier, and SVM algorithms, achieved accuracy values exceeding 80%.	They still face limitations in achieving the same level of accuracy different conditions in the dataset.
Ahmed A. Esmail, Sayed M. Abdallah et al.,	Detecting sentiment in text data effectively. Introducing a novel architecture for emotional nuance capture.	Semantic Emotion Neural Network (SENN) model outperforms existing models in accuracy and quality, demonstrating robust performance metrics.	Diversities of text formats complicate emotion analysis automation
Suhasini and Srinivasu	Detect emotion based on tweets using ML Models NB KNN.	Accuracy 72.5%.	No Contextual Information Applied.
De Bruyne et al.	ML Models SVM Logistic Regression RF Multi-level emotion classification was used for tweets.	Accuracy 52%.	Unbalanced data.
Baziotis et al.	Deep Learning Bi-LSTM used for Emotion Detection in Tweets	Accuracy 58.40%.	Problem for out of vocabulary words.
Ezen-Can and Ethem	Deep Learning Bi-GRU Various classification for Tweet post.	Jaccard Accuracy 40.00%.	No application of affected lexicons.
Krommyda	Deep Learning Models were used for emotion detection from social media	Accuracy 91.9%.	Trust Emotion have Low Accuracy.
Kratzwald et al.,	Random Forest SVM Bi-LSTM Deep Learning Model were used.	F1 Score 23.2%.	Small dataset.
Rathnayaka et al.,	Deep Learning Bi-GRU Attention Network used for Emotion detection in Microblogs.	F1 Score 58.00%.	Emotion detection in Microblogs.
Shrivastava et al.,	Deep Learning CNN Max Pooling Emotion detection in multimedia text.	F1 Score 72.48%.	There is a overlap between few classes.
Ameer et al.	ML, deep learning, transfer learning used for Emotion Classification	F1 Score 67%	Limited ML and transfer learning performance.
Ameer et al.	Transfer learning used for Emotion Classification	F1 Score 62.4%	incapable of simulating how words and classes relate to one another

REFERENCES

[1] S. Indhumathi and F. Mary Harin Fernandez, "Evaluating sentiment analysis algorithms with varied datasets: A machine learning approach," in *Proc. International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS)*, 2024. IEEE Xplore Part No. CFP242B2-ART, ISBN: 979-8-3315-1809-7.

[2] J. Olivares Lopez and A. Sánchez Lopez, "Machine learning techniques for sentiment analysis," *International Journal of Combinatorial Optimization Problems and Informatics*, vol. 15, no. 5, pp. 6–16, Dec. 2024, ISSN: 2007-1558.

[3] Esmail, S. M. et al., "Textual emotion recognition: Advancements and insights," in *Proc. 6th Conference on Novel Intelligent and Leading Emerging Sciences (NILES)*, Oct. 2024.

[4] F. Mary Harin Fernandez, T. V. Ramana, and S. Lakumarapu, "Integrating supervised and probabilistic learning: A hybrid SVM-Naive Bayes framework for enhanced emotional insight extraction from Twitter streams," in *Proc. International Conference on Communication and Electronics Systems (ICCES)*, 2024. IEEE Xplore Part No. CFP24AWO-ART, ISBN: 979-8-3503-7797-2.

[5] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams Engineering Journal*, vol. 5, no. 4, pp. 1093–1113, 2014.

[6] Ameer, N. Ashraf, G. Sidorov, and H. Gómez Adorno, "Multilabel emotion classification using content-based features in Twitter," *Computación y Sistemas*, vol. 24, no. 3, pp. 1159–1164, 2020.

[7] Ameer, G. Sidorov, H. Gómez Adorno, and R. Nawab, "Multi-label emotion classification on code-mixed text: Data and methods," *IEEE Access*, vol. 10, pp. 8779–8789, 2022.

[8] S. Mohammad, F. Bravo-Marquez, M. Salameh, and S. Kiritchenko, "SemEval-2018 task 1: Affect in tweets," in *Proc. 12th International Workshop on Semantic Evaluation*, 2018, pp. 1–17.

[9] Ameer, C. P. Capetillo, H. Gómez-Adorno, and G. Sidorov, "Automatic fake news detection in Urdu language using transformers," in *CEUR Workshop Proceedings*, vol. 3159, pp. 1127–1134, 2021.

[10] M. Arif, A. L. Tonja, I. Ameer, O. Kolesnikova, A. Gelbukh, G. Sidorov, and A. G. M. Meque, "CIC at CheckThat! 2022: Multi-class and crosslingual fake news detection," in *Working Notes of CLEF*, 2022.

[11] Pervaz, I. Ameer, A. Sittar, and R. M. A. Nawab, "Identification of author personality traits using stylistic features: Notebook for PAN at CLEF 2015," in *CLEF (Working Notes)*, 2015, pp. 1–7.

[12] Sittar and I. Ameer, "Multi-lingual author profiling using stylistic features," in *FIRE (Working Notes)*, 2018, pp. 240–246.

[13] Ameer, G. Sidorov, and R. M. A. Nawab, "Author profiling for age and gender using combinations of features of various types," *Journal of Intelligent & Fuzzy Systems*, vol. 36, no. 5, pp. 4833–4843, 2019.

[14] Ameer and G. Sidorov, "Author profiling using texts in social networks," in *Handbook of Research on Natural Language Processing and Smart Service Systems*. IGI Global, 2021, pp. 245–265.

[15] M. H. F. Siddiqui, I. Ameer, A. F. Gelbukh, and G. Sidorov, "Bots and gender profiling on Twitter," in *CLEF (Working Notes)*, 2019.

[16] Ameer, M. H. F. Siddiqui, G. Sidorov, and A. Gelbukh, "CIC at SemEval-2019 task 5: Simple yet very efficient approach to hate speech detection, aggressive behaviour detection, and target classification in Twitter," in *Proc. 13th International Workshop on Semantic Evaluation*, 2019, pp. 382–386.

[17] S. Volet, C. Seghezzi, and S. Ritchie, "Positive emotions in student-led collaborative science activities: Relating types and sources of emotions to engagement in learning," *Studies in Higher Education*, vol. 44, no. 10, pp. 1734–1746, 2019.

[18] C. Malighetti, S. Sciara, A. Chirico, and G. Riva, "Emotional expression of body on Instagram," *social media + Society*, vol. 6, no. 2, Art. no. 2056305120924771, 2020.

[19] S. Al Ajrawi, A. Agrawal, H. Mangal, K.

Putluri, B. Reid, G. Hanna, and M. Sarkar, "Evaluating business Yelp's star ratings using sentiment analysis," *Procedia Computer Science*. [Publication details incomplete.]

[20] Z. Drus and H. Khalid, "Sentiment analysis in social media and its application: Systematic literature review," *Procedia Computer Science*, vol. 161, pp. 707–714, 2019.

[21] K. Garcia and L. Berton, "Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA," *Applied Soft Computing*, vol. 101, Art. no. 107057, 2021.

[22] Ameer, M. Arif, G. Sidorov, H. Gómez-Adorno, and A. Gelbukh, "Mental illness classification on social media texts using deep learning and transfer learning," *arXiv preprint* arXiv:2207.01012, 2022.

[23] P. Bhardwaj, P. Gupta, H. Panwar, M. K. Siddiqui, R. Morales-Menendez, and A. Bhaik, "Application of deep learning on student engagement in e-learning environments," *Computers & Electrical Engineering*, vol. 93, Art. no. 107277, 2021.

[24] T. Dixon, "'Emotion': The history of a keyword in crisis," *Emotion Review*, vol. 4, no. 4, pp. 338–344, 2012.

[25] Bakker, T. van der Voordt, P. Vink, and J. de Boon, "Pleasure, arousal, dominance: Mehrabian and Russell revisited," *Current Psychology*, vol. 33, no. 3, pp. 405–421, 2014.

[26] R. Plutchik, "A general psychoevolutionary theory of emotion," in *Theories of Emotion*. Elsevier, 1980, pp. 3–33.

[27] S. Mohammad and P. Turney, "NRC emotion lexicon," National Research Council of Canada, Tech. Rep., 2013.

[28] W. S. Ark, D. C. Dryer, and D. J. Lu, "The emotion mouse," in *Proc. HCI International*, vol. 1, 1999, pp. 818–823.

[29] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "SMOTE: Synthetic minority over-sampling technique," *Journal of Artificial Intelligence Research*, vol. 16, pp. 321–357, 2002.

[30] K. W. Fischer, P. R. Shaver, and P. Carnochan, "How emotions develop and how they organise development," *Cognition and Emotion*, vol. 4, no. 2, pp. 81–127, 1990.

[31] S. Tomkins, *Affect Imagery Consciousness*, vol. 1, *The Positive Affects*. New York, NY, USA: Springer Publishing Company, 1962.

[32] S. Zad, M. Heidari, H. James, Jr., and O. Uzuner, "Emotion detection of textual data: An interdisciplinary survey," in *Proc. IEEE World AI IoT Congress (AIIoT)*, 2021, pp. 255–261.

[33] R. C. Balabantaray, M. Mohammad, and N. Sharma, "Multi-class Twitter emotion classification: A new approach," *International Journal of Applied Information Systems*, vol. 4, no. 1, pp. 48–53, 2012.

[34] Z. Li, H. Xie, G. Cheng, and Q. Li, "Word-level emotion distribution with two schemas for short text emotion classification," *Knowledge-Based Systems*, vol. 227, Art. no. 107163, 2021.

[35] N. Braun, C. van der Lee, L. Gatti, M. Goudbeek, and E. Krahmer, "MemoFC: Introducing the multilingual emotional football corpus," *Language Resources and Evaluation*, vol. 55, no. 2, pp. 389–430, 2021.

[36] W. Khan, S. Ali, U. K. Muhammad, M. Jawad, M. Ali, and R. Nawaz, "AdaDiffGrad: An adaptive batch size implementation technique for DiffGrad optimization method," in *Proc. 14th International Conference on Innovations in Information Technology (IIT)*, 2020, pp. 209–214.

[37] M. Hasan, E. Rundensteiner, and E. Agu, "Automatic emotion detection in text streams by analyzing Twitter data," *International Journal of Data Science and Analytics*, vol. 7, no. 1, pp. 35–51, 2019.

[38] M. Suhasini and B. Srinivasu, "Emotion detection framework for Twitter data using supervised classifiers," in *Data Engineering and Communication Technology*. Singapore: Springer, 2020, pp. 565–576.

[39] M. Z. Asghar, F. Subhan, M. Imran, F. M. Kundi, S. Shamshirband, A. Mosavi, P. Csiba, and A. R. Várkonyi-Kóczy, "Performance evaluation of supervised machine learning techniques for efficient detection of emotions from online content," *arXiv preprint* arXiv:1908.01587, 2019.

[40] S. Y. M. Lee and Z. Wang, "Multi-view learning for emotion detection in code-switching texts," in *Proc. International*

Conference on Asian Language Processing (IALP), 2015, pp. 90–93.

[41] M. Allouch, A. Azaria, R. Azoulay, E. Ben-Izchak, M. Zwilling, and D. A. Zachor, "Automatic detection of insulting sentences in conversation," in *Proc. IEEE International Conference on the Science of Electrical Engineering in Israel (ICSEE)*, 2018, pp. 1–4.

[42] L. Wikarsa and S. N. Thahir, "A text mining application of emotion classifications of Twitter's users using Naive Bayes method," in *Proc. 1st International Conference on Wireless and Telematics (ICWT)*, 2015, pp. 1–6.

[43] Amjad, L. Khan, and H.-T. Chang, "Semi-natural and spontaneous speech recognition using deep neural networks with hybrid features unification," *Processes*, vol. 9, no. 12, Art. no. 2286, 2021.

[44] Majeed, H. Mujtaba, and M. O. Beg, "Emotion detection in Roman Urdu text using machine learning," in *Proc. 35th IEEE/ACM International Conference on Automated Software Engineering Workshops*, 2020, pp. 125–130.

[45] S. X. Mashal and K. Asnani, "Emotion intensity detection for social media data," in *Proc. International Conference on Computing Methodologies and Communication (ICCMC)*, 2017, pp. 155–158.

[46] H. Nida, K. Mahira, M. Mudasir, M. Mudasir Ahmed, and M. Mohsin, "Automatic emotion classifier," in *Progress in Advanced Computing and Intelligent Engineering*. Singapore: Springer, 2019, pp. 565–572.

[47] F. Murat, O. Yildirim, M. Talo, U. B. Baloglu, Y. Demir, and U. R. Acharya, "Application of deep learning techniques for heartbeats detection using ECG signals—analysis and review," *Computers in Biology and Medicine*, vol. 120, Art. no. 103726, 2020.

[48] Chatterjee, U. Gupta, M. K. Chinnakotla, R. Srikanth, M. Galley, and P. Agrawal, "Understanding emotions in text using deep learning and big data," *Computers in Human Behavior*, vol. 93, pp. 309–317, 2019.

[49] M. Krommyda, A. Rigos, K. Bouklas, and A. Amditis, "An experimental analysis of data annotation methodologies for emotion detection in short text posted on social media," *Informatics*, vol. 8, no. 1, Art. no. 19, 2021.

[50] K. Dashtipour, M. Gogate, J. Li, F. Jiang, B. Kong, and A. Hussain, "A hybrid Persian sentiment analysis framework: Integrating dependency grammar-based rules and deep neural networks," *Neurocomputing*, vol. 380, pp. 1–10, 2020.

[51] M. Abdullah, M. Hadzikadicy, and S. Shaikhz, "SEDAT: Sentiment and emotion detection in Arabic text using CNN-LSTM deep learning," in *Proc. 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 2018, pp. 835–840.

[52] J. Huang, Z. Lin, and X. Liu, "Episodic memory network with self-attention for emotion detection," in *Proc. International Conference on Database Systems for Advanced Applications*. Singapore: Springer, 2019, pp. 220–224.

[53] M. Polignano, P. Basile, M. De Gemmis, G. Semeraro, and V. Basile, "AlBERTo: Italian BERT language understanding model for NLP challenging tasks based on tweets," in *Proc. 6th Italian Conference on Computational Linguistics (CLiC-it)*, vol. 2481, 2019, pp. 1–6.

[54] Ameer, N. Bölücü, M. H. F. Siddiqui, B. Can, G. Sidorov, and A. Gelbukh, "Multi-label emotion classification in texts using transfer learning," *Expert Systems with Applications*, Art. no. 118534, 2022.

[55] J. Xiao, "Figure Eight at SemEval-2019 task 3: Ensemble of transfer learning methods for contextual emotion detection," in *Proc. 13th International Workshop on Semantic Evaluation*, Minneapolis, MN, USA, Jun. 2019, pp. 220–224.

[56] J. Choudrie and Y. K. Dwivedi, "Investigating factors influencing adoption of broadband in the household," *Journal of Computer Information Systems*, vol. 46, no. 4, 2006.

[57] L. De Bruyne, O. De Clercq, and V. Hoste, "LT3 at SemEval-2018 task 1: A classifier chain to detect emotions in tweets," in *Proc. 12th International Workshop on Semantic Evaluation*, 2018, pp. 123–127.

[58] Baziotis, N. Pelekis, and C. Doulkeridis, "DataStories at SemEval-2017 task 4: Deep LSTM with attention for message-level and topic-based sentiment analysis," in *Proc. 11th*

International Workshop on Semantic Evaluation (SemEval-2017), 2017, pp. 747–754.

[59] Ezen-Can and E. F. Can, "RNN for affects at SemEval-2018 task 1: Formulating affect identification as a binary classification problem," in *Proc. 12th International Workshop on Semantic Evaluation*, 2018, pp. 162–166.

[60] P. Rathnayaka, S. Abeysinghe, C. Samarajeewa, I. Manchanayake, M. J. Walpola, R. Nawaratne, T. Bandaragoda, and D. Alahakoon, "Gated recurrent neural network approach for multilabel emotion detection in microblogs," *arXiv preprint* arXiv:1907.07653, 2019.

[61] M. Krommyda, A. Rigos, K. Bouklas, and A. Amditis, "An experimental analysis of data annotation methodologies for emotion detection in short text posted on social media," *Informatics*, vol. 8, no. 1, 2021.

[62] Kratzwald, S. Ilić, M. Kraus, S. Feuerriegel, and H. Prendinger, "Deep learning for affective computing: Text-based emotion recognition in decision support," *Decision Support Systems*, vol. 115, pp. 24–35, 2018.