International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I6P206

Volume 71 Issue 6, 47-53, June 2023

Original Article

Emotions-Based Sentiment Analysis using Fusion-Based Learning Model

Penubaka Balaji[1], D. Haritha[2], Konatham Sumalatha[3], D. Uma Priya[4], Rudramani Bhutia[5], Rahul Kumar[6]

[1,2,5,6]*Department of CSE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India.*
[3,4]*School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamilnadu, India.*

[1]*Corresponding Author : penubakabalaji.cse@gmail.com*

Received: 27 March 2023 Revised: 30 May 2023 Accepted: 14 June 2023 Published: 25 June 2023

Abstract *- Emotions-based sentiment analysis using fusion-based learning models uses artificial intelligence (AI) techniques to identify and analyze emotions associated with a particular text or speech. This approach involves using machine learning (ML) algorithms to fuse multiple sources of information, including linguistic features, acoustic features, and contextual information, to determine the sentiment of a particular text or speech. The aim of the proposed approach is utilized to find accurate sentiments by combining several models. The fusion-based learning model (FBLM) combines various data types to better represent the sentiment expressed in the text or speech. Several steps are involved in the FBLM approach, including data preparation, extracting features, combining features, and emotions classification. In the data preprocessing stage, the input data is cleaned and standardized to remove irrelevant information. In the feature extraction step, linguistic, acoustic, and contextual features are extracted from the text or speech. In the feature fusion step, the extracted features are combined using various fusion techniques to create a more comprehensive representation of the sentiment expressed in the text or speech. Finally, in the sentiment classification step, linear regression (LR) is used to classify the opinion of the text or speech. The proposed approach has several advantages over traditional sentiment analysis techniques, including higher accuracy, more comprehensive sentiment analysis, and the ability to analyze emotions associated with specific words or phrases. The approach has potential applications in various fields, including analysis of social media (ASM), user comments analysis, and online market analysis.*

Keywords *- Machine Learning (ML), Sentiment Analysis (SA), Fusion-based learning, Classification.*

1. Introduction

Sentiment analysis is the domain that extracts sentiments from several emotions and text messages. Deep learning (DL) techniques have shown great promise in improving the accuracy of sentiment analysis models [1]. One challenge in sentiment analysis is the availability of labeled data, which is necessary for training supervised learning models [2]. This technique can overcome the scarcity of labeled data, which is often a problem in sentiment analysis. Text data augmentation focuses on generating new inputs by applying various transformations to the existing text data [3]. These transformations can include adding synonyms or antonyms, changing word order, replacing words with their synonyms or related terms, and other methods. By applying these transformations, new samples can be generated that are similar to the original data but have slight variations in the text [4].

DL techniques, such as neural networks, can be trained on augmented data to improve the accuracy of SA models. Text data augmentation is a powerful technique for improving sentiment analysis model accuracy. DL techniques, such as neural networks, can be trained on augmented data to enhance the performance of sentiment analysis models [5]. As the amount of text data grows, these techniques will become increasingly crucial for analyzing large datasets and extracting meaningful insights [6].

With the advent of big data, sentiment analysis has become an indispensable tool for businesses and organizations seeking to understand their customers' opinions and attitudes. When analyzing big data, sentiment analysis can be performed using various techniques, including ML algorithms and natural language processing (NLP) [7]. These techniques allow for the study of vast amounts of data quickly and accurately. One of the challenges in sentiment analysis of big data is ensuring the accuracy of the results. ML and NLP techniques require extensive training and validation to guarantee reliability and accuracy [8].

Additionally, the quality of the data being analyzed can impact the accuracy of the sentiment analysis results. Data cleaning and preprocessing techniques may need to be applied to remove noise and irrelevant information before performing sentiment analysis [9].

Fig. 1 Types of emotions

1.1. Contribution

The contribution of this research mainly focused on the following conditions:

- The proposed model focused on extracting the accurate and best features to find emotions using emojis and text.
- An effective preprocessing is used to remove the unwanted text from the given dataset.
- By combining all these models, effective sentiments are analyzed based on advanced classification.
- The proposed model can work on four real-time datasets.

2. Literature Survey

P. K. Jain et al. [10] introduced a sentiment-based analysis that extracts the sentiments from various reviews collected from reviews and ratings based on user recommendations. The proposed work focused on extracting the sentiments from airline services. Firstly, the LSTM was applied to the dataset to analyze the sentiments. Secondly, aspect-based sentiments are estimated based on ratings. Finally, these two show better sentiments on airline datasets. The sentiment analysis helps the airlines to improve ticket sales and the quality of services. P. Liu et al. [11] introduced a sentiment analysis approach that helps to increase the E-commerce business based on sales. The sales of the products are analyzed based on the Quality function deployment (QFD). The effectiveness of the QFD is improved by combining the Kano model and analysis [25] on social media to extract the sentiments from the Chinese E-commerce approach. The result shows that the introduced model gives a good analysis. F. Faturohman et al. [12] introduced a new model that extracts sentiments from Twitter data about health conditions. The data belongs to government servants from Indonesian countries, and insurance companies use data based on reviews given by the people. The accuracy of the sentiment analysis is 86.87%. R. Setchi et al. [13] proposed a new linkage between user reviews and images that analyze sentiments. The aim of this proposed linkage model mainly focused on extracting the sentiments from text and images. The proposed model extracts the schemes from text and image data implemented by an ontology-based algorithm. The comprehensive data were collected from 40 participants about two popular products. Results show that sentiments are extracted from various real-time datasets.

X. Lei et al. [29] proposed the SBRP given to online products. The proposed approach focused on solving the overloading issue in data. The proposed approach develops a better understanding system to understand the reviews based on the user's preferences and gives an accurate recommendation about the product. SBRP mainly follows two types; such calculation of sentimental analysis based on the user's sentiment belongs to every product. The second one is to consider the attributes belongs to influence every user. The proposed approach divides the sentiments based on user preferences, which helps to show a better recommendation system. Z. -J. Zha et al. [15] proposed an aspect-based ranking framework that dynamically finds the significant aspects based on online product reviews. Based on several analyses, the proposed approach achieved better results, like analyzing the enormous reviews belonging to large products. The opinions and aspects significantly impact the total reviews given to the products. The dataset belongs to 21 popular products with eight categories that show the potential proposed models. X. Chen et al. [16] proposed the soft computing-based sentiment analysis that solves various issues in sentiment recommender systems. The recommender system focused on developing the biblio parameters and systemic topic modeling (STM) that shows better results belongs to topic modeling. I. Gupta et al. [17] proposed a hybrid linguistic model that improves the strength of the polarity based on the total words. The proposed model is a classification model that classifies Twitter data based on its features. The dataset is a Twitter dataset called SemEval-2013 Task 2. S. Davis et al. [18] proposed a new sentiment extraction model for E-commerce applications [26]. The experiments were analyzed by collecting data from 2010 to 2020. The dataset is Amazon data [30] based on rental vacation homes. M. S. Akhtar et al. [19] introduced a stacked-based model that predicts the effectiveness of the sentiments and emotions from real-time datasets. H. Peng et al. [20] proposed the DISA model based on reinforcement learning. DISA can extract special symbols from the Chinese language called phonetic features. Y. Ma et al. [21] introduced a fusion-based approach that combines the integrated model. By using the BiLSTM approach, the significant features from the dataset. C. Wang et al. [22] proposed the tree-based LSTM that extracts the sentiments from document datasets.

3. XLNet Pre-trained Model for Sentiment Analysis

XLNet is a state-of-the-art language model that extends the Transformer architecture with several innovations, including the permutation language modeling objective (PLMO) and the use of two-stream self-attention. Here are the key equations that define XLNet:

3.1. PML Objective

The PMLO is a novel training objective that aims to maximize the expected log-likelihood of all possible permutations of the input sequence. The objective is defined as follows:

$$\mathcal{L}\mathrm{PLM}(\theta) = \mathrm{E}\pi\sim\mathrm{Perm}(z)\left[\sum_{i=0}^{T}\log p(\mathrm{X}_{\pi i}|\mathrm{X}\pi < i, h\pi, \theta)\right], \quad (1)$$

Where $z = x_1, \ldots\ldots, x_T$ is the input sequence, πrandom permutation of the indices, $1, \ldots, T$, $p(X_{\pi i}|X\pi < i, h\pi, \theta)$ is the conditional probability of the i^{th}token is given its previous tokens and the hidden states of all tokens in the sequence, and θdenotes the model parameters. The expectation is taken over all possible permutations of z.

3.2. Two-Stream Self-Attention

XLNet employs two-stream self-awareness to identify prerequisites among all tokens held pairs in the sequence of inputs while preventing the drawbacks of autoregressive frameworks such as the transform. The mechanism of two-stream self-attention is defined as follows:

$$Q = [q_1, \ldots q_T], K = [k_1, \ldots, k_T], V = [v_1, \ldots., v_T], \quad (2)$$

$$Z^{fwd} = \mathrm{softmax}\left(Q^{fwd}K^{fwdT}\right)V^{fwd}, \quad (3)$$

$$Z^{bwd} = \mathrm{softmax}\left(Q^{bwd}K^{bwdT}\right)V^{bwd}, \quad (4)$$

$$Z_i = \left[Z_i^{fwd};\ Z_i^{bwd}\right] \quad (5)$$

Where Q^{fwd}, K^{fwd}, and $V^{fwd}$are the query, key, and value matrices for the forward stream, $Q^{bwd}K^{bwdT}$, and V^{bwd} are the query, key, and value matrices for the backward stream, [. ; .] denotes concatenation along the feature dimension, and Z_i is the output representation for the i^{th} token. The self-attention weights are computed separately.

3.3. Text Preprocessing

In this step, text data is cleaned and prepared for analysis. It converts the raw text data into the proposed model in understandable language. Here are some common preprocessing techniques for text cleaning [27]:

3.3.1. Tokenization

Divide the words into text, known as tokens.

3.3.2. Stop-word Removal

Eliminating the common words such as “the”, “a”, “and”, etc., that frequently occur in a text but do not provide much meaning.

3.3.3. Stemming and Lemmatization

Reducing words to their base form, known as the stem or lemma, ensures that words with the same root are treated as the same word.

3.3.4. Removing Special Characters and Numbers

Removing special characters, numbers, and punctuation from the text.

3.3.5. Spell Checking and Correction

Correcting spelling errors and typos in the text data.

3.3.6. Removing HTML Tags

HTML tags should remove from the given inputs.

3.3.7. Removing URLs

URLs should be removed from text reviews

3.3.8. Removing Stop-Words in Different Languages

If the text is in different languages, stop-words for each language should be removed.

By applying these techniques, the proposed model quality and accuracy of text data and help your ML algorithms better to understand the meaning and context of the text.

4. Term Frequency-Inverse Document Frequency (TF-IDF)

TF-IDF is used in TM and NLP to extract features. It is a statistical metric that indicates the significance of a term in a review or corpus.

TF (term frequency) computes the TF present in the document, and IDF computes the same terms across the corpus. The score of a term is obtained by multiplying its TF and IDF values.

The equation for determining a term's TF-IDF score in a review is as follows:

$$\mathrm{TF} - \mathrm{IDF} = \mathrm{TF}(\mathrm{term}, \mathrm{document}) * \mathrm{IDF}(\mathrm{term}, \mathrm{corpus})$$

TF denotes the frequency of the term in the reviews, and IDF indicates the reverse of the reviews frequency of the word in the corpus.

The aim of TF-IDF is to find more significant words or phrases from the reviews or documents, which is called the feature extraction method.

Terms with elevated TF-IDF scores are more likely to be informative and discriminative features in a given task, such as classification, clustering, or information retrieval.

There are several variations of the basic TF-IDF formula, such as smoothed IDF, sublinear scaling of TF, and normalization of TF-IDF vectors. These variations can improve the performance of TF-IDF for different applications and datasets.

5. Bag-of-Words (BoW) Model

Several mathematical feature extraction models exist for sentiment analysis, but one popular approach is the BoW model.

In the BoW model, a document (or, in the case of sentiment analysis, a piece of text) is represented as a vector of word counts. Each word in the text is treated as a feature, and the count of the occurrences of each word in the text is the corresponding value in the vector.

To perform sentiment analysis using the BoW model, we first need to create a corpus of texts that have been labeled with their corresponding sentiment (e.g., positive, negative, or neutral). Then, we create a vocabulary by selecting the most frequent words across all the texts in the corpus. Finally, we represent each text in the corpus as a vector of word counts, where the values correspond to the frequency of each word in the vocabulary.

Once we have represented the texts as vectors, we can apply machine learning algorithms to classify them into different sentiment categories. Common algorithms used for sentiment analysis include LR, SVM, and NN.

In addition to the BoW model, other feature extraction methods for sentiment analysis include n-grams, word embeddings, and topic modeling. Every model has its own advantages and drawbacks based on the given application and dataset.

6. Fusion Based Sentiment Analysis Model (FBSAM)

The FBSAM integrates multiple sources or features. It can combine different models, such as machine learning, lexicon-based, or rule-based, to capture a broader range of sentiment information. The goal is to capitalize on the strengths of each model to generate more accurate sentiment predictions.

Logistic regression (LR) is a statistical model frequently used for binary classification tasks like sentiment analysis. Based on a set of input features, it predicts the likelihood of an input belonging to a specific class (positive or negative sentiment in this case). A logistic function models the relationship between the input features (e.g., TF-IDF or BoW representations) and the target sentiment label. The logistic regression model learns to make sentiment predictions based on input features by training on labeled data.

- Assign labels to the training data. Positive reviews were initialized as 1, and negative ones were initialized as 0.
- Train a logistic regression model on the labeled data.
- Predict the sentiment of new reviews using the trained model. The predicted sentiment score is between 0 and 1, with higher values indicating a positive feeling and good emotion and lower values indicating a negative sentiment and destructive emotion.

The logistic regression algorithm can be expressed mathematically as follows:

Given a set of features X and labels y, the logistic regression model learns the weights w that minimize the loss function L(w):

$$\mathrm{L(w)} = -\frac{1}{\mathrm{m}} * \mathrm{sum}\big(\mathrm{y} * \log\big(\mathrm{h(x)}\big) + (1-\mathrm{y}) * \log\big(1-\mathrm{h(x)}\big)\big) \tag{6}$$

Where:
'm' is the total training samples.
'h(x)' is the sigmoid function that maps the features to a probability score between 0 and 1
'w' is the weight vector that determines the importance of each feature in predicting the sentiment
'y' is the binary label (1 for positive sentiment and 0 for negative sentiment) for each training example.

7. Dataset Description

7.1. Amazon Dataset

This dataset is an online E-commerce dataset that contains training and testing. The training contains three million records, while the testing set has four lakh records from 568,000 customers. These reviews are given by various users based on online products. It is a free and open-source dataset from Kaggle.

7.2. Ebay Dataset

The eBay dataset was generated as a component of a data science Bootcamp assignment. The proposed model aims to create the best sentiment analysis model possible. The author created this dataset using Python web scraping scripts for research purposes. This dataset is divided into two files, the first of which contains four attributes. There are 44757 instances in total. An attribute's rating is represented by an integer value ranging from one to five. The second file is preprocessed with three features: rating, title review, and content review.

7.3. Trip-Advisor

It consists of 20k hotel customer reviews. These reviews are pulled from TripAdvisor and collected from the Kaggle website.

7.4. IMDB Movies Dataset

It contains 50,000 movie reviews, 40,000 testing data points, and 10,000 training data points. The IMDB movie review dataset, which includes 25,000 positive and 25,000 negative reviews.

A comprehensive and practical approach combines fusion-based sentiment analysis, TF-IDF, BoW, and LR. While TF-IDF and BoW capture important textual features and LR provides a reliable classification algorithm for sentiment prediction, the fusion approach combines the best features of multiple models.

7.5. Performance Evaluation

This section analyzes the proposed model's performance based on the confusion matrix's analysis and count values. The attributes are listed below:

True Positive (TP)	True Negative (TN)
False Positive (FP)	False Negative (FN)

TP: If the actual value is correct, the estimated value is also correct.
TN: If the actual value is incorrect, then the actual value is also incorrect.
FP: If the original value is incorrect, then the estimated value is correct.
FN: If the actual value is correct, then the predicted value is incorrect.

Based on the above values, the parameters are given below:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{8}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

$$\text{Specificity} = \frac{\text{No of TN}}{\text{No of TN} + \text{No of FP}} \tag{10}$$

$$\text{F1} - \text{Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{11}$$

Table 1. List of algorithms used to analyze on amazon dataset

Models	Precision	Accuracy	Recall	Specificity	F1-Score
MDM [22]	88.23	88.12	87.5	89.12	88.6
FBS [23]	92.45	93.23	92.2	92.56	93.4
FBLM	99.56	99.23	98.3	99.89	99.1

Table 2. List of algorithms used to analyze on ebay dataset

Models	Precision	Accuracy	Recall	Specificity	F1-Score
MDM [22]	88.34	89.23	88.5	88.98	89.2
FBS[23]	91.45	91.45	93.4	93.56	92.4
FBLM	98.34	98.56	97.3	98.34	97.4

Table 3. List of algorithms used to analyze on Trip-advisor dataset

Models	Precision	Accuracy	Recall	Specificity	F1-Score
MDM [22]	90.34	91.43	90.78	90.67	90.54
FBS [23]	92.87	92.9	92.67	92.65	92.67
FBLM	98.56	99.23	99.56	99.76	99.45

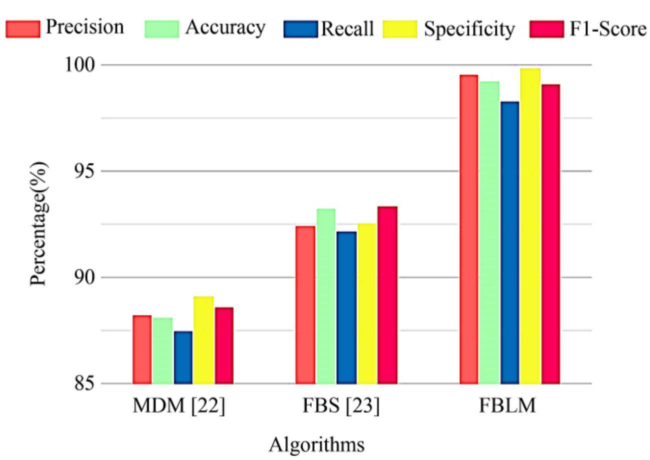

Fig. 2 List of algorithms performance on amazon dataset

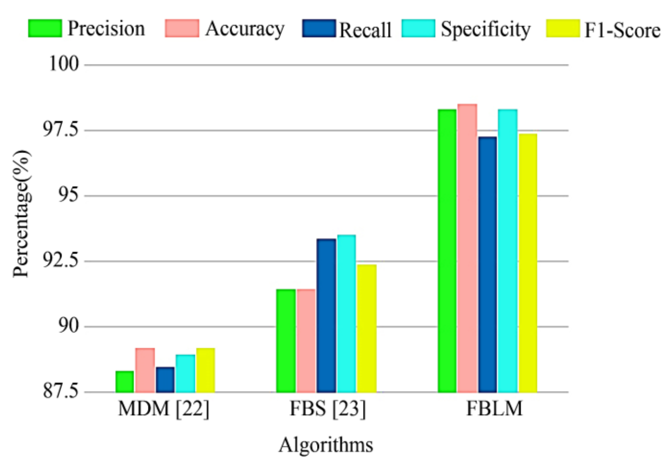

Fig. 3 List of algorithms performance on ebay dataset

Table 4. List of algorithms used to analyze on IMDB dataset

Models	Precision	Accuracy	Recall	Specificity	F1-Score
MDM [22]	93.67	93.67	93.9	93.45	93.34
FBS [23]	94.87	93.4	94.5	94.8	93.76
FBLM	99.8	99.8	99.7	99.3	99.43

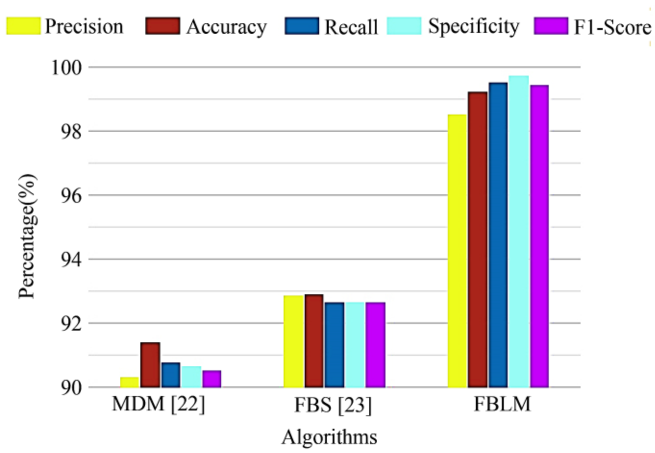

Fig. 4 List of algorithms performance on Trip-advisor

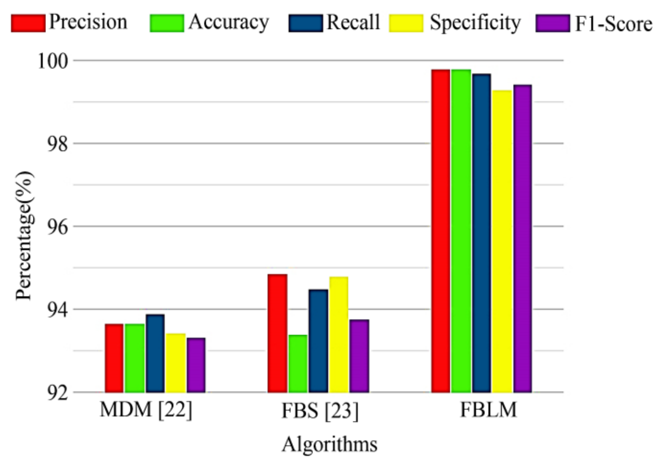

Fig. 5 List of algorithms performance on dataset

8. Conclusion

The fusion-based learning model (FBLM) is a machine learning approach that combines multiple data sources to improve prediction accuracy. In emotion-based sentiment analysis, FBLM can integrate various data types such as text, audio, and video to predict sentiment more accurately. Through FBLM, sentiment analysis improved by incorporating more diverse and affluent forms of data. FBLM can capture more nuanced emotions and produce more accurate sentiment analysis results. In conclusion, FBLM is a significant approach for emotion-based sentiment analysis as it allows for the integration of multiple sources of data to improve prediction accuracy. In the future, more advanced FBLM models will be developed that can accurately predict sentiment from a broader range of data sources.

References

[1] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436-44, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[2] Hugo Queiroz Abonizio, Emerson Cabrera Paraiso, and Sylvio Barbon, "Toward Text Data Augmentation for Sentiment Analysis," *IEEE Transactions on Artificial Intelligence*, vol. 3, no. 5, pp. 657-668, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Shahid Shayaa et al., "Sentiment Analysis of Big Data: Methods Applications and Open Challenges," *IEEE Access*, vol. 6, pp. 37807-37827, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[4] Lei Zhang, Shuai Wang, and Bing Liu, "Deep Learning for Sentiment Analysis: A Survey," *Wiley Interdisciplinary Reviews Data Mining Knowledge Discovery*, vol. 8, no. 4, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[5] Alex M.G. Almeida et al., "Applying Multi-Label Techniques in Emotion Identification of Short Texts," *Neurocomputing*, vol. 320, pp. 35-46, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] Shuteng Niu et al., "A Decade Survey of Transfer Learning," *IEEE Transactions on Artificial Intelligence*, vol. 1, no. 2, pp. 151-166, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] Rahul Gupta, "Data Augmentation for Low Resource Sentiment Analysis using Generative Adversarial Networks," *IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 7380-7384, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Siddhaling Urolagin, and Saifali Patel, "User-Specific Loyalty Measure and Prediction Using Deep Neural Network from Twitter Data," *IEEE Transactions on Computational Social Systems*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Praphula Kumar Jain et al., "Unscrambling Customer Recommendations: A Novel LSTM Ensemble Approach in Airline Recommendation Prediction Using Online Reviews," *IEEE Transactions on Computational Social Systems*, vol. 9, no. 6, pp. 1777-1784, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Peide Liu et al., "A Big Data-Kano and SNA-CRP Based QFD Model: Application to Product Design Under Chinese New E-commerce Model," *IEEE Transactions on Engineering Management*, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Faisal Faturohman, Budhi Irawan, and Casi Setianingsih, "Sentiment Analysis on Social Security Administrator for Health Using Recurrent Neural Network," *4th International Seminar on Research of Information Technology and Intelligent Systems*, Yogyakarta, Indonesia, pp. 575-580, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Rossitza Setchi, and Obokhai K. Asikhia, "Exploring User Experience with Image Schemas, Sentiments, and Semantics," *IEEE Transactions on Affective Computing*, vol. 10, no. 2, pp. 182-195, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] Xiaojiang Lei, Xueming Qian, and Guoshuai Zhao, "Rating Prediction Based on Social Sentiment from Textual Reviews," *IEEE Transactions on Multimedia*, vol. 18, no. 9, pp. 1910-1921, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[14] Palaniammal, and P. Anandababu, "Robust Sarcasm Detection using Artificial Rabbits Optimizer with Multilayer Convolutional Encoder-Decoder Neural Network on Social Media," *SSRG International Journal of Electronics and Communication Engineering*, vol. 10, no. 5, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Xieling Chen et al., "A Bibliometric Review of Soft Computing for Recommender Systems and Sentiment Analysis," *IEEE Transactions on Artificial Intelligence*, vol. 3, no. 5, pp. 642-656, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Itisha Gupta, and Nisheeth Joshi, "Feature-Based Twitter Sentiment Analysis With Improved Negation Handling," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 4, pp. 917-927, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] Storm Davis, and Nasseh Tabrizi, "Customer Review Analysis: A Systematic Review," *IEEE/ACIS 6th International Conference on Big Data, Cloud Computing, and Data Science*, Zhuhai, China, pp. 91-97, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Md Shad Akhtar, Asif Ekbal, and Erik Cambria, "How Intense Are You? Predicting Intensities of Emotions and Sentiments using Stacked Ensemble," *IEEE Computational Intelligence Magazine,* vol. 15, no. 1, pp. 64-75, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] Haiyun Peng et al., "Phonetic-Enriched Text Representation for Chinese Sentiment Analysis with Reinforcement Learning," *Information Fusion*, vol. 70, pp. 88-99, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Yaohong Ma, Hong Fan, and Cheng Zhao, "Feature-Based Fusion Adversarial Recurrent Neural Networks for Text Sentiment Classification," *IEEE Access*, vol. 7, pp. 132542-132551, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[21] Chang Wang, Bang Wang, and Minghua Xu, "Tree-Structured Neural Networks with Topic Attention for Social Emotion Classification," *IEEE Access*, vol. 7, pp. 95505-95515, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[22] Penubaka Balaji, O. Nagaraju, and D. Haritha, "CommTrust: Reputation based Trust Evaluation in E-Commerce Applications," *International Conference on Big Data Analytics and Computational Intelligence*, pp. 318-323, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[23] Penubaka Balaji, D. Haritha, and O. Nagaraju, "Feature Based Summarization System for E-Commerce Based Products by Using Customers Reviews," *Computing Communications and Data Engineering Series*, vol. 1, no. 3, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[24] Francisca Onaolapo Oladipo, Ogunsanya Funmilayo Blessing, and Ezendu Ariwa, "Terrorism Detection Model using Naive Bayes Classifier," *SSRG International Journal of Computer Science and Engineering,* vol. 7, no. 12, pp. 9-15, 2020. [CrossRef] [Publisher Link]

[25] Balaji Penubaka, D. Haritha, and O. Nagaraju, “Opinion Mining Based Reputational Trust Assessment in E-Commerce Applications,” *Journal of Advanced Research in Dynamical and Control Systems,* vol. 10, no. 3, 2018. [Google Scholar]

[26] K Sumalatha, and M. S. Anbarasi, "A Review on Various Optimization Techniques of Resource Provisioning in Cloud Computing," *International Journal of Electrical and Computer Engineering*, vol. 9, no. 1, pp. 629-634, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[27] Haritha Donavalli, and Balaji Penubaka, “Identification of opinionated Features Extraction from Unstructured Textual Reviews,” *International Journal of Recent Technology and Engineering,* vol. 7, pp. 674-677, 2019. [Publisher Link]

[28] R. Bharathi, R. Bhavani, and R. Priya, "Leveraging Deep Learning Models for Automated Aspect Based Sentiment Analysis and Classification," *SSRG International Journal of Electrical and Electronics Engineering,* vol. 10, no. 5, pp. 120-130, 2023. [CrossRef] [Publisher Link]

[29] Zheng-Jun Zha et al., "Product Aspect Ranking and its Applications," *IEEE Transactions on Knowledge and Data Engineering,* vol. 26, no. 5, pp. 1211-1224, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[30] Konatham Sumalatha, and M. S. Anbarasi, “Cloud Service Selection Using Fuzzy ANP,” Behera, P.K., Sethi, P.C. (eds) Digital Democracy – IT for Change, CSI 2020, *Communications in Computer and Information Science,* Springer, Singapore, vol. 1372, 2021. [CrossRef] [Google Scholar] [Publisher Link]