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| **Sr. No** | **Title of Paper** | **Name of Authors** | **Published Year** | **Remarks/Findings** |
| 1 | Distantly Supervised Lifelong Learning for Large-Scale Social Media Sentiment Analysis | Rui Xia , Jie Jiang, and Huihui He | **2017** | * This framework is designed to address challenges related to continuously changing topics and increasing text data in social media sentiment analysis * Methodology: Leveraging lifelong learning techniques, including sequential learning, Lifelong Bagging, and Lifelong Stacking, to boost sentiment analysis performance on social media data. * Evaluation showcases effectiveness on large-scale and benchmark datasets. |
| 2. | Anomaly Detection through Enhanced Sentiment Analysis on Social Media Data | Zhaoxia WANG, Victor Joo Chuan TONG, Xin XIN, Hoong Chor CHIN | 2006 | * Stresses the critical role of anomaly detection in social media sentiment analysis, highlighting the risks of overlooking abnormal sentiments within extensive datasets. * Components include sequential learning, lifelong sentiment evaluation, Lifelong Bagging, and Lifelong Stacking. * References Naïve Bayes, Maximum Entropy, and Support Vector Machine as employed algorithms in sentiment analysis for categorizing text into positive, negative, or neutral sentiments. |
| 3. | Sentiment Analysis of Twitter Dat | Apoorv Agarwal ,Boyi Xie, Ilia, Vovsha OwenRambow, RebeccaPassonneau | 2011 | * Introducing POS-specific prior polarity features and utilizing a tree kernel to enhance sentiment analysis accuracy. Experimenting with three models - unigram, feature-based, and tree kernel-based models. * Creating new resources like emoticon and acronym dictionaries for preprocessing Twitter data. * Employing Support Vector Machines (SVM) and 5-fold cross-validation for model performance assessment. Assessing the importance of features, particularly those related to prior polarity of words and parts-of-speech tags, in enhancing sentiment classification accuracy. |
| 4. | Twitter Sentiment Classification using Distant Supervision | Alec Go, Richa Bhayani, Lei Huang |  | ML Algorithm Advantages/Disadvantages:   * Naive Bayes: Simple, efficient for large datasets, but assumes feature independence. * MaxEnt: Handles feature overlap, versatile, but may require more training data * SVM: Effective in high-dimensional spaces, versatile, but memory-intensive and computationally complex. |
| 5. | Study on Machine learning based Social Media and Sentiment analysis for medical data applications | R. Meena1, Dr. V. Thulasi Bai2 | 2019 | * Social media platforms like Twitter and Google Trends produce extensive health-related data.Sentiment analysis is applied to analyze health-related queries and sentiments on these platforms. * Sentiment analysis provides valuable insights into public opinions and perceptions related to healthcare.Machine learning algorithms and statistical methods are employed for sentiment analysis in social media data. |
| 6. | Combining Lexicon-based and Learning-based Methods for Twitter Sentiment Analysis | Lei Zhang, Riddhiman Ghosh, Mohamed Dekhil, Meichun Hsu, Bing Liu | 2011 | * The proposed method in the paper combines a lexicon-based approach with machine learning techniques to improve recall and F-score in sentiment analysis on Twitter data. * The method first uses a lexicon-based approach for entity-level sentiment analysis, then automatically identifies additional opinionated tweets to train a classifier for assigning polarities to entities, resulting in improved performance compared to state-of-the-art baselines. |
| 7. | Aspect-level Sentiment Analysis for Social Media Data in the Political Domain using Hierarchical Attention and Position Embeddings | Renny Pradina Kusumawardani, Muhammad Wildan Maulidani | 2020 | * The document concentrates on deep learning architectures for aspect-level sentiment analysis in the political domain using social media data.   **Algorithms Used**:   * + Hierarchical Attention and Position Embeddings: Employed in the deep learning architecture.   + LSTM: Achieved superior accuracy compared to GRU and RNN.   + Trainable Word2Vec Embeddings: Trained on Bahasa Indonesia social media data, enhancing accuracy. |
| 8. | Multilingual Sentiment Analysis on Social Media Disaster Data | Muhammad Jauharul Fuady, Roliana Ibrahim1 | 2020 | * Utilizes deep learning for sentiment analysis and compares it with a lexicon-based approach using Sentiwordnet for English and Sentiwordnet-Bahasa for Malay. * Deep learning model achieves higher accuracy and F1-score compared to the lexicon-based approach. Multilingual sentiment classifier shows reasonable accuracy during disaster periods. Word embeddings capture semantic relationships in English and Malay datasets. * Study demonstrates the effectiveness of deep learning, especially in multilingual contexts, for sentiment analysis during disasters, highlighting advantages over lexicon-based methods. |
| 9. | Deep Learning for Automated Sentiment Analysis of Social Media | Li-Chen Cheng †, Song-Lin Tsai | 2019 | * Utilizes deep learning models including LSTM, BiLSTM, and GRUs for sentiment analysis on social media data. * Deep learning frameworks offer innovative approaches for handling social media language nuances. Models like BiLSTM demonstrate superior accuracy, precision, recall, and F1 score. RNNs and LSTM networks efficiently model sequential data. |
| 10. | TagNet: Toward Tag-based Sentiment Analysis of Large Social Media Data | Yang Chen | 2018 | * Utilizes a lexicon-based approach and Support Vector Machine (SVM) for sentiment analysis. Lexicon-based approach offers simplicity and interpretability. SVM provides high accuracy and robustness. * Lexicon-based approach may struggle with context-dependent sentiment. SVM requires labeled data and may not handle unbalanced datasets optimally.Suggests combining lexicon-based and learning-based approaches for sentiment analysis to leverage strengths of both methodsTop of Form |
| 11. | Robust Sentiment Detection on Twitter from Biased and Noisy Data | Luciano Barbosa, Junlan Feng | 2010 | * Utilizes a 2-step sentiment analysis process, incorporating meta-information and tweet syntax features, with data from sentiment detection websites. * Implements a Subjectivity Classifier and Polarity Classifier to handle biased and noisy data from multiple sources. * Demonstrates robustness in handling biased and noisy data. Abstract representations and limited feature sets contribute to improved accuracy and efficiency. |