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Performance Analysis Of Machine Learning Techniques For Sentiment Analysis:A Review

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Abstract: Sentiment analysis, often a common topic of study in the nexus of NLP and ML is opinion mining. Computing techniques are used to analyse text for a sense of the author's emotional state. The capacity of machine learning methods to identify patterns and extract relevant characteristics from textual input has made them promising for use in sentiment analysis jobs. This paper offers a detailed comparison of the relative performance among the several machine learning methods that have been used for sentiment analysis jobs. We describe the metrics that measure how well different strategies perform across different domains and datasets, weigh their benefits and drawbacks, and provide insights into how well they perform overall. The goal of this research is to assist academics and professionals in selecting the top machine learning techniques for sentiment analysis tasks based on their particular requirements.

Keywords: sentiment analysis, public opinion, domains, and datasets etc.

Introduction:

Sentiment analysis, often known as opinion mining, is a fast-expanding field of NLP and machine learning. As more and more people share their thoughts and experiences online via social media, product reviews, and other channels, the importance of sentiment analysis in deciphering public opinion, consumer feedback, and market trends has grown. Sentiment analysis is the method of determining a text's level of positivity, negativity, or neutrality using computers. Machine learning techniques hold great potential for sentiment analysis tasks because they can automatically recognise patterns and extract pertinent information from text input.These methods make it possible to create scalable and accurate sentiment analysis models that can handle massive amounts of text data with little resources. Many different machine learning algorithms and methods, each with its own advantages and disadvantages, have been suggested and used to sentiment analysis jobs as the field has developed.

Through an in-depth analysis of these techniques, we will examine their performance metrics, strengths, limitations, and suitability for different domains and datasets. By understanding the comparative performance of these algorithms, researchers and practitioners can make informed decisions when selecting appropriate machine learning techniques for sentiment analysis tasks based on their specific requirements. This review will discuss hybrid approaches that combine supervised and unsupervised techniques, as well as ensemble learning methods and transfer learning for sentiment analysis. We will also address the challenges faced in sentiment analysis, such as handling sarcasm, irony, and negation, domain adaptation, multilingual sentiment analysis, and the need for explain ability and interpretability in sentiment analysis models.

By This review aims to contribute to the advancement of sentiment analysis research by providing an overview of the current state of the field and highlighting areas for improvement. It also aims to help researchers and practitioners make wise choices when utilising machine learning techniques for sentiment analysis tasks.

Review Literature:

(Kabir et al., 2021) studied “An empirical research on sentiment analysis using machine learning approaches” and said that Social media users want to remark on products and services, therefore user-generated content is rising. Their social media reviews assist customers choose products and services. Machine learning dominates sentiment analysis. This research analyses prominent machine learning methods. Online user assessments from several industry categories evaluate these tactics. The research leverages several Amazon, Yelp, and IMDb data sets. Experiments use support vector machines, decision trees, bagging, boosting, random forests, and maximum entropy. Users may utilise review data sets for business intelligence and product sales, and more advanced machine learning algorithms like boosting and maximum entropy can recognise attitudes in online user assessments.

(Samal et al., 2017) studied “Performance analysis of supervised machine learning techniques for sentiment analysis” and said that Internet and online apps like feedback gathering systems are making individuals smarter. In these apps, users provide reviews on movies, goods, services, and more for future reference. Machines find identifying good and negative input tiresome. Machine Learning Techniques train and make the machine intelligent so it can detect the feedback kind and provide additional advantages and features for web apps and consumers. Choosing the best supervised machine learning approach is tough since there are numerous. This study collects movie review datasets of various sizes and trains the model using standard supervised machine learning methods. so, the model can classify the review. Python's NLTK, WinPython, and Spyder process movie reviews. Python's sklearn library trains and evaluates the model.

(Saberi& Saad, n.d.) studied “Sentiment Analysis or Opinion Mining” and said that It is potential to Opinion mining (OM) or emotional analysis is the process of finding, extracting, and categorising opinions about anything (SA). It is a kind of natural language processing oversight (NLP). public opinion towards a certain law, strategy, advertising campaign, etc. It comprises developing a technique for collecting and analysing opinions expressed on social media on regulations, laws, policies, etc. Information extraction is crucial since it is both a difficult activity and a valuable tool. This suggests that automated opinion-mining approaches are required in order to extract sentiment from a piece of material on the global web. Modern approaches include sentiment analysis, lexical-based methods, and supervised and unsupervised machine learning. The major goal of this paper is to survey sentiment analysis (SA) and opinion mining (OM) methodologies, two separate but related techniques. With references to the work of earlier researchers, it also covers the sentiment analysis's application areas and difficulties.

(Pasumpon Pandian, 2021) studied “Performance Evaluation and Comparison using Deep Learning Techniques in Sentiment Analysis” and said that Sentiment analysis is a popular deep learning application. This work improves automated feature extraction. Traditional methods like surface approach involve the complex manual feature extraction procedure that drives feature-driven breakthroughs. These methods will help establish feature predictability and provide a solid foundation for deep learning. Deep learning is used in the proposed research to extract features. There are three main points to this research. First, create deep learning sentiment classifiers to compare performance. The final sources are obtained using ensemble methods and information merging. The final phase categorises models, including the proposed model, using ensembles. Finally, experimental analysis and performance recording establish the optimal model relative to the deep learning baseline.
(Mehta et al., 2018) studied “Performance Evaluation of Machine Learning and Deep Learning Techniques for Sentiment Analysis” and said that Researchers have been studying sentiment analysis as a natural language processing application since the rise of opinion-based online content. A lot of progress has helped text data categorization. In this research, we optimised parameters for popular classical classifiers, deep neural networks, and their hybrid combinations to maximise classification accuracy. Our tests on tagged movie review corpus yielded significant findings and comparisons.
(Heller et al., 2008) studied “The role of perspective in identifying domains of reference” and said that We tested whether listeners can distinguish employing the contrastive expectation linked to scalar adjectives, real-time reference resolution may distinguish between public and private information. Our findings demonstrate that listeners made advantage of this differential from the very beginning to focus their list of probable referents to items with different areas of commonality. The divide between common and privileged knowledge is employed without being prompted by peculiar situations, which extends earlier research that suggests ground information affects real-time language processing.
(NishaJebaseeli&Kirubakaran, 2012) studied “A Survey on Sentiment Analysis” and said that the internet becomes a valuable platform for online education, idea exchange, and product or service reviews with the use of wireless technologies. Online evaluations for a product or service may number in the millions, making it difficult to monitor and understand customer feedback. A recent area of research called sentiment analysis employs text analytics, computational linguistics, and natural language processing to categorise the polarity of ideas stated and extract subjective information from sources. This study offers a complete investigation of sentiment analysis and opinion mining with regard to product reviews.
(Asghar et al., 2014) studied “Feature Extraction in Sentiment Analysis” and said the goal of Using sentiment analysis, commonly referred to as opinion mining, one may learn what other people have said and thought. It was developed as a consequence of the rapid increase in internet users, the impact of social media, and the emergence of online review sites. Sentiment or opinion refers to publicly generated material having a political or legal undertone. Many times, individuals are curious as to what aspects of a product or service other others like and find annoying. As a result, sentiment analysis is essential to understanding a product's attributes or qualities. Feature extraction in sentiment analysis is now a prominent research subject in addition to the considerable work in text analytics. Methods and tools for feature extraction in sentiment

analysis and opinion mining are reviewed in this article. We used a methodical approach to analysing the literature in order to identify the topics that have gotten the most scholarly attention and bring more focus to the topics that have received the least. To emphasise the necessity for more study, we also attempted to identify the most and least prevalent feature selection strategies.

(Shamantha et al., 2019) studied "Sentiment Analysis Using Machine Learning Classifiers: Evaluation of Performance" and said that Opinions are shared on the modern internet via social media, microblogging, review websites, and personal blogs. Sentiment analysis, a part of text mining, rates how enthusiastic an author is about a topic. Here, a keyword is used to look through tweets or reviews and determine how positive or negative they are. Tweet sentiment is measured by the careful selection of scoring words. In order to find the most effective features, a Naive Bayes Classifier (NBC) is trained and tested on word features and the polarity of tweet sentiment. Accuracy, precision, and processing time are compared across three different machine learning classifiers: Random Forest, Naive Bayes, and Support Vector Machine (SVM)

According to a 2015 study by (Murthy), "Are tweets about elections pre-emptive, reactive, or just a buzz?"Sentiment analysis is the investigation of feelings and opinions expressed in text. Opinion mining is another term for the process of analysing user opinion. When trying to convey the feelings of a large population, a small group, or an individual, data sentiment analysis is a powerful tool. This technique is used to determine how someone feels about a tangible object. Tweets, blogs, status updates, posts, etc., on social media and other online platforms contain vast volumes of information that may be mined for insights. Several statistical techniques, such as Naive Bayes, K-Nearest Neighbor, and Random Forest, were used to the movie reviews in this study.

(Dubey et al., 2016) studied "A research study of sentiment analysis and various techniques of Sentiment analysis" and claimed that Sentiment analysis, often known as opinion mining, is a method for objectively categorising and rating the views of others. People nowadays construct concepts and beliefs by either algorithmic or human analysis of data and the perspectives of others. Since everything can now be found online, internet use has become integral to everyday life. As a consequence, it is used to discuss trade, business, opinions, love, support, and other aspects of the human condition. Since the rise of social media, a number of websites have emerged, including blogs, forums, reviews, and social networks. On these sites, users may share their thoughts and opinions on products as well as make lists of their favourite and least favourite features (same or different feature). These reviews are gathered, looked at, and their basic perspective is identified. This survey study encompasses all terms and concepts relevant to opinion mining and focuses on a thorough investigation of the topic. This page also discusses how reviews are put together, how to identify evaluations' semantic orientation, and how to identify phrases with subjectivity in them (Ezeli & Sebastiani, 2006).

(M. Ahmad et al., 2017) studied "Hybrid Tools and Techniques for Sentiment Analysis" and said that theSentiment analysis and Opinion mining are related ideas. Numerous methods have been used to investigate these topics in length. Emotions in texts are categorised as good, negative, or neutral using these techniques. Tweets, Facebook status updates, user comments on specific issues, and reviews of products, television shows, and movies are all examples of information sources that might be useful. Executives in business may apply sentiment analysis methods on this kind of information to make forecasts and plans for the future. Spelling and grammatical problems, as well as incorrect punctuation, are commonplace since the data comes from a variety of sources and is dependent on the user, who might be located anywhere in the globe. Several techniques for sentiment analysis exist, each of which can automatically classify and arrange the data. Hybrid methods, Lexicon-based methods, and Machine Learning-based methods may be separated out as distinct categories. Combining machine learning with lexicon-based approaches frequently yields the best results. In this study, we explored and analysed a wide variety of hybrid approaches and tools.

(Hussein, 2018) studied "A survey on sentiment analysis challenges" and said that writers are increasingly producing reviews, opinions, suggestions, ratings, and feedback as websites, social networks, blogs, and online portals proliferate. This author may have written emotional stuff about several things, including persons, hotels, objects, and events. These mindsets are very advantageous for organisations, governments, and people in general. The vast majority of this content was generated by writers, and while it must be mined using text mining and sentiment analysis techniques, its primary purpose is education. However, the study and assessment of sentiment presents several difficulties. Because of these obstacles, accurately assessing the polarity of emotions and appreciating the significance of feelings is sometimes challenging. Sentiment analysis is a technique for finding and extracting irrational information from texts via the use of text analysis and technology for natural language processing. This paper describes the challenges that sentiment analysis faces in terms of its methodologies and practises.

(Tubishat et al., 2018) studied "Implicit aspect extraction in sentiment analysis" and said that the process of identifying sentiment words by extracting feature/aspect or opinion words. Semantic orientation, a subset of text classification, includes sentiment analysis. Aspect extraction, either for implicit or explicit aspects, is the main goal of aspect-level sentiment analysis. Because of sentiment analysis's widespread use, several methods for eliciting latent characteristics have emerged. Although implicit aspect extraction has received considerable attention in the literature, explicit aspect extraction has been the primary emphasis. This article offers a thorough analysis of implicit aspect/feature extraction methods. The first point of view compares the current implicit word extraction methods and provides a short overview of each approach. The second point of view involves categorising and contrasting the datasets, languages, and drawbacks of the available methods. Only 45 of the roughly 50 articles on implicit aspect extraction that were taken into consideration for this research from 2005 to 2016 were looked at and analysed. Around 64 percent of the 45 papers on implicit aspects extraction were created by researchers who largely depend on unsupervised methods, with supervised methods coming in second with around 27 percent of the total. Semi-supervised techniques make up the remaining 9%. The fact that 25 papers performed research using just product reviews and 5 studies utilising product reviews in conjunction with other forms of data indicates that product review datasets are the most often employed when compared to other data sources. In addition, English and Chinese have received greater attention in studies on the extraction of implicit aspect elements than other languages. Finally, this analysis offers suggestions for unresolved issues and new lines of inquiry.

(S. R. Ahmad et al., 2019) studied "feature selection techniques in sentiment analysis" and said that the fast expansion of web development has changed how people communicate nowadays. Results from sentiment analysis (SA) may be precise, significant, and of high quality when features and associated sentiment words (SWs) are combined. There are certain fundamental concepts in the study of SA that must be grasped, including the entities or objects that are central to the debate, their traits or qualities, the SWs, and the relationship between these SWs and the traits of the object. The accuracy and significance of the SA findings may be affected if these fundamental issues are not addressed. This review's primary goals are to provide aaa general explanation of feature selection's objectives and techniques, as well as techniques for finding SWs and figuring out how features connect to SWs. The work's primary contributions are a systematic organisation of current articles about FS approaches and the naming of SWs. New findings from South African researchers are also highlighted. The potential of the metaheuristic approach to overcome feature selection issues in SA will also be investigated, as will the pros and cons of current FS approaches.

(Darwich et al., 2019) studied "Corpus-Based Techniques for Sentiment Lexicon Generation" and said that the most essential element driving the effectiveness of contemporary sentiment analysis systems is a sentiment lexicon. This tool is essential for occupations involving sentiment analysis and greatly improves them. This is shown by the expansion of a significant body of research devoted to the development of automated sentiment lexicon generating systems. Dictionary-based and corpus-based labelling are the two basic approaches for semantically orienting subjective concepts. In contrast to the latter, which relies on co-occurrence data or hidden grammatical patterns in text corpora, the former involves tagging words using an online lexicon. The outcome is a linguistic resource with a priori knowledge of words across the semantic dimension of emotion. The most well-known works that produce sentiment lexicons using corpus-based techniques are summarised in this article. We also Comparatively evaluate the performance of cutting-edge algorithms developed for this purpose, shedding light on current advancements and difficulties.

(Mehta & Pandya, 2020) studied "Sentiment Analysis Methodologies, Practices AndApplications" and said that When examining material in textual form and attempting to glean ideas from the text, sentiment analysis is a technique that is sometimes applied. It is often referred to as mining sensations or emotions. Twitter, Facebook, YouTube, and other online communication tools have grown in significance in contemporary culture. People talk about it and express their feelings or thoughts. In this review article, we prefer to focus on the area of online data mining and machine learning known as opinion mining, also known as emotion assessment. In this research, the outcomes of an analysis employing several ML and Lexicon inquiry methods are presented. Results are assessed in order to carry out an evaluation study and confirm the composition estimate. Future scholars will benefit from understanding the present developments in this arrangement of possibility appraisal.

Machine Learning Techniques:

In order to detect patterns and generate predictions on unread material, machine learning methods have been frequently used for sentiment analysis applications. We will talk about a few of the well-known supervised approaches for sentiment analysis using machine learning.

- **Naïve Bayes Classifier:** The probabilistic Naïve Bayes classifier uses Bayes' theorem. It assumes feature independence and estimates a text's emotion class likelihood. Sentiment analysis often uses computationally efficient Naïve Bayes classifiers. They may fail to capture complicated feature connections and suffer from naïve feature independence.

- **Support Vector Machines (SVM):**Support Vector machines are robust classifiers that look for the best hyperplane to divide data into distinct emotional categories.SVMs can capture complicated decision boundaries and work well with high-dimensional feature spaces. Since they can process both linear and non-linearly separable data, they have proven useful in sentiment analysis applications.
- **Decision Trees and Random Forests:** Decision Trees iteratively partition data by most informative attributes. Each internal node tests a feature, and each leaf node predicts a sentiment class. Decision Trees can handle numerical and categorical information and are intuitive. Random Forests, which integrate decision trees, increase generalisation, and decrease overfitting.
- **Neural Networks:** In recent years, sentiment analysis has been dominated by neural networks, particularly deep learning architectures. RNNs, CNNs, and transformer-based designs like BERT have shown state-of-the-art performance. Neural Networks excel in learning complicated representations from raw text material, capturing contextual information, and modelling long-range relationships.

Challenges and Future Directions:

While supervised machine learning techniques have shown promising results in sentiment analysis, several challenges remain. In this section, we discuss some of the key challenges and potential future directions in the field.

- **Handling Sarcasm, Irony, and Negation:** Sentiment analysis models often struggle with detecting and interpreting sarcasm, irony, and negation in text. Misclassification is one result of these language occurrences, which may also impact the reliability of sentiment analysis tools. Improving the accuracy of sentiment analysis models will need more study to build algorithms that can properly recognise and interpret such subtle sentiments.
- **Domain Adaptation and Transfer Learning:**Models used for sentiment analysis in one field may not be applicable in another. Methods for domain adaptation allow models to be adapted to unlabelled domains. Transfer learning improves sentiment analysis by using models already learned on large datasets. More research is needed on domain adaptation and transfer learning for sentiment analysis across domains and languages.
- **Multilingual Sentiment Analysis:** As sentiment analysis expands globally, the need for accurate multilingual sentiment analysis becomes crucial. Challenges in multilingual sentiment analysis include language-specific nuances, code-switching, and data scarcity for certain languages. Strong multilingual sentiment analysis algorithms that can accommodate a wide range of languages and cultural settings should be the focus of future study.
- **Explain ability and Interpretability:** As sentiment analysis models are increasingly deployed in critical applications, there is a growing demand for explain ability and interpretability. Users and stakeholders need to understand how and why a model made a particular sentiment prediction. Future

research should focus on developing methods to explain the decisions made by sentiment analysis models, providing transparency and accountability.

- **Handling Biases:**Unfair or biased conclusions may be drawn from sentiment analysis models if there are biases in the underlying training data. To guarantee fairness and lessen the influence of biases in sentiment analysis algorithms, future study should focus on bias identification and mitigation strategies.
- **Real-Time and Dynamic Sentiment Analysis:** Traditional sentiment analysis models often process text in a batch manner, which may not be suitable for real-time applications such as social media monitoring. Future research should focus on developing real-time and dynamic sentiment analysis techniques that can handle streaming data and provide timely insights.

Conclusion:

Sentiment analysis helps comprehend public opinion, client feedback, and market trends. This review article analyses machine learning sentiment analysis methodologies. We addressed Naïve Bayes classifier, their applicability for sentiment analysis tasks depends on the dataset and its needs.We also discussed sentiment analysis issues and future prospects, including managing sarcasm, irony, and denial, domain adaptation and transfer learning, multilingual sentiment analysis, explain ability and interpretability, biases, and real-time and dynamic sentiment analysis. These issues show that sentiment analysis models require further study and development to increase accuracy, robustness, and fairness. The dataset, labelled data, computing resources, and performance-interpretability trade-offs should influence sentiment analysis machine learning algorithm selection. This review article helps academics and for sentiment analysis, practitioners favour machine learning techniquesby revealing their merits, weaknesses, and performance measures.

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