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Comparative analysis of ML and DL techniques on aspect-based sentiment analysis

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ABSTRACT

The user generated data on the web from blogs, web forums and social networking sites has become so enormous and extracting useful information from them has become an interesting research topic in recent years. Aspect Based Sentiment Analysis (ABSA) detect the feature which is nothing but aspect from the information and then apply sentiment analysis on that feature. The subtask of ABSA is Aspect Extraction, assigning Polarity to Aspects and Aspect and Aspect Sentiment Classification. Initially various Machine learning algorithms like Conditional Random Forest (CRF), Naive bayes, Decision Trees and Support Vector Machine (SVM) were used to implement the subtask of ABSA. Then with the introduction of deep learning algorithms like RNN, LSTM and transformers the efficacy of Aspect based Sentiment analysis were improved. In this paper we provide a comparative study between ML and DL approaches to improve overall performance of Aspect based Sentiment analysis.

KEY WORDS

Machine learning; Deep learning; Vector machines; Random forest; Support vector machine

ARTICLE HISTORY

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Introduction

Machine learning, in its most basic sense, is any kind of computer program that does not require explicit human programming to "learn" on its own. In "Computing Machinery and Intelligence," he discussed his renowned "Learning Machine," which had the ability to trick a person into thinking it was real [1]. These days, big data analytics and data mining programs come under the spectrum of machine learning, a phrase that is commonly used in these fields. Machine learning algorithms are the "brains" behind most predictive programs, such as spam filters, product recommenders, and fraud detectors. The machine learning stages as shown in Fig 1 can be input, feature extraction, classification and output. The distinctions between semi-supervised learning, which blends supervised and unsupervised approaches, ensemble modelling, which employs a variety of approaches, and supervised machine learning are all understood by data scientists.

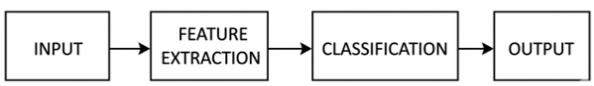

Figure 1. Machine learning stages.

Using known and labelled datasets, the user teaches the program to produce an answer in supervised learning. For supervised learning tasks, classification and regression methods such as support vector machines, decision trees, and random forests are used. Algorithms in unsupervised machine learning produce results on unlabeled and unknown data. Unsupervised approaches are frequently used by data scientists to find patterns in fresh data sets. K-means and other clustering methods are frequently employed in unsupervised machine learning [1]. A variety of platforms and programming languages, such as Java, Python, Scala, and others, can be used by data scientists to create machine learning algorithms. To speed up the process, they can also make use of pre-built machine learning frameworks. Mahout is one such framework that was well-liked on Apache Hadoop, and Apache Spark's MLlib library is now a standard.

The multiple layers that are incorporated into deep learning models which are essentially neural networks are what give deep learning its "deep" quality. Many layers of models can make up a Convolutional Neural Network (CNN), with each layer receiving input from the layer before it. processes it, then sends data in a daisy-chain way to the following layer. Many interpreted the historic victory of a CNN created by Google's DeepMind team over the human world champion in the ancient Chinese game of Go as evidence of the ascendancy of deep learning.

These days, deep learning is very popular for two major reasons. Initially, it was found that CNNs operate considerably quicker on GPUs, including the Tesla K80 CPU from NVidia. Second, data scientists discovered that the enormous amounts of data we have been gathering may be used as an enormous training resource. corpus, and consequently boost the CNNs to produce considerable gains in computer vision and natural language processing algorithm accuracy. A software development framework that is gaining popularity is Tensorflow; other examples are Caffe, Torch, and Theano. Tensorflow is a product of Google. Advances in deep learning utilizing CNNs on GPUs are largely responsible for the progress made in the development of self-driving cars [1]. This has the mutual benefit of spurring future advancements in deep learning and the broader area of artificial intelligence. Figure 2 shows the stages of Deep Learning as input, feature extraction and classification, and finally output.

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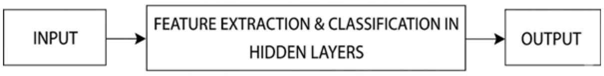

Figure 2. Deep learning stages.

Because of the growth of web there is an exponential increase in the user generated content on the internet. A subject becomes phenomenon when more people share their views online on the same topics [2]. ABSA provides sentiment of collective aspect either single aspect or multiple of any domain rather than defining sentiment of whole domain itself [3]. As compared with other types of sentiment analysis, ABSA provides more elaborate and revealing solution to sentiment analysis [1]. Aspect Extraction refers to the extraction and identification of an item or feature that is the subject of an opinion expressed in the text. It also refers to recognizing the important qualities of entities referenced in the text, if any. ASC stands for Aspect-Sentiment Classification, and it is the process of determining the polarity or sentiment score related to a particular aspect. When sentiment analysis focuses on (often pre-defined) latent subjects or concepts and necessitates categorizing aspect words, some research further employs Aspect-Category Detection (ACD) and Aspect Category Sentiment Analysis (ACSA) as an extension. Using traditional approaches, the features linked with the aspects were manually sketched out, resulting in a laborious and error-prone process. Nevertheless, as artificial intelligence advances, these limitations might be surmounted. Thus, researchers are increasingly employing AI-based Machine Learning (ML) and deep learning (DL) techniques to improve the efficacy of ABSA [4].

Literature Review

In SemEval -2016, Abhishek Sethi and Pushpak Bhattacharyya investigated the ABSA task as a shared task, and different methods for completing these subtasks are explained. They also discussed the most detailed method of examining viewpoints [5]. A fresh methodology was provided by Ms. Anuradha N. Nawate et al. for determining the essential components of the objects being considered [6]. Features that are linguistically connected reveal both the positive and negative qualities of something. To handle ABSA, a multilabel classifier is used. An RNN-based method is used to ascertain sentiments for extracted aspects in an end-to-end ABSA. The machine learning method yields 90% accuracy, whereas with multiple cross-validation, the deep learning algorithm yields 96% accuracy.

Gianni Brauwers and Flavius Frasincar in their survey they reviewed the quickly changing condition of Aspect-Based Sentiment Classification (ABSC) research. The ABSC models are divided into three main groups by a novel taxonomy that is proposed: knowledge-based, machine learning, and hybrid models. Together with this taxonomy, there is a summary [7]. The highlights of the model performances that have been published, together with explanations of the several ABSC models that are both clear and technical. The most recent ABSC models including transformer model-based models and hybrid deep learning models with knowledge bases were covered. A study of different methods for expressing the model inputs and assessing the model outputs were also included. Additionally, patterns in the ABSC research are noted, and future directions for the field's advancement are discussed.

Haoyue Liu et al., suggested the modern approaches for resolving an aspect-based sentiment analysis issue. There are now three popular approaches: lexicon-driven, both deep learning and conventional machine learning techniques. We present a comparative overview of the most recent deep learning techniques in this survey article. The effectiveness of the current deep learning techniques, evaluation criteria, and several widely used benchmark data sets are presented. In conclusion, current issues and potential avenues for future study are showcased and examined [8].

Abu Kowshir Bitto et al., conducted a sentiment analysis on customer feedback on the Food Panda, HungryNaki, Pathao Food, and Shohoz Food Facebook pages, and information was gathered from the comments on these four websites. Before the model was put into practice for the Natural Language Processing (NLP) task, we underwent a thorough data pre-processing procedure that included steps like tokenizing, deleting stop words, adding contractions, and more. Extreme Gradient Boosting (XGB), Random Forest Classifier (RFC), Decision Tree Classifier (DTC), and multinominal Naive Bayes (MNB) are the four supervised classification algorithms used. Convolutional neural network (CNN), Long Short-Term Memory (LSTM), and Recurrent Neural Network (RNN) are the Three deep learning models that are employed. With an accuracy of 89.64%, the XGB model outperforms all four machine learning techniques [9].

According to Ashish Kumar et al., aspect-based sentiment analysis aims to determine a review of a sentence's sentiment polarity with respect to a specified aspect. LSTM, GRU, and RNN are examples of deep learning sequential models that represent the state-of-the-art in sentiment polarity inference. The contextual relationship between the words in a review phrase can be effectively captured using these techniques. These techniques, however, are not very effective at capturing long-term dependencies. By concentrating just on the most important portion of the text, the attention mechanism performs an important function. Aspect location is important in the ABSA instance. Words that are close to an aspect have a greater influence on how people feel about it. As a result, we provide a technique that supports the attention mechanism and uses a dependency parsing tree to extract position-based information. The performance of the deep learning model is improved when this kind of position information is used instead of a straightforward word-distance-based location. We used the SemEval'14 dataset for the studies to show how dependency parsing relation-based attention affects ABSA [10].

According to Dinesh Kumar et al., because of the steady increase in social media users over the past few decades, sentiment analysis has drawn a lot of attention from scholars. Both billions and millions of people use social media platforms like Facebook, Instagram, Twitter, and others to share and express their ideas, opinions, and beliefs about various goods, services, and businesses. To identify characteristics in sentences or phrases, commonly used classification algorithms are examined and categorized in this work. Since ABSA is the primary topic of this paper, we looked over a few of the most recent publications that dealt with the subject. Following the completion of the review, it is noted that in the past, textual features were manually extracted in order to determine their polarity [9]. However, manual feature extraction from texts proves to be challenging due to the exponential expansion of data over the last few decades. As a result, scientists cleared the path for artificial intelligence. We examined current ABSA techniques under the two categories of ML-based ABSA and DL-based ABSA in order to comprehend the idea of ABSA in the context of AI. Review findings indicate that most of the time,

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ML-based binary classifiers Support Vector Machine (SVM) and tree techniques like Decision Tree, RandomForest, and NaiveBayes were utilized.

Because these strategies are straightforward and simple to apply, researchers can use them in their work to analyze elements in sentences, phrases, or comments. SVM's inability to function properly when there are several aspects in the text is one of its main disadvantages, whereas tree-based algorithms can become unstable due to little changes in the data [9]. Furthermore, ML algorithms tend to lose a lot of information during the pre-processing and feature extraction stages and were unable to manage the vast and complex datasets. Researchers turned to DL-based methods to get around these problems. In their work, a significant number of experts employed CNN, RNN-based LSTM, and Bi-LSTM because of their capacity to automatically extract features from text. Although deep learning techniques can process enormous datasets with efficiency, their high error susceptibility and massive training data requirements have a negative impact on the accuracy of textual aspect detection. Ultimately, it can be said that using hybrid deep learning techniques to common datasets can increase the precision of emotion detection. The problems that follow demonstrate that sentiment analysis is still an area of growing research interest.

In order to assist manufacturing businesses in making better decisions, the article by D. Pavithra et al., offers a complete examination of aspect-based sentiment analysis (ABSA) and its levels. It does this by looking at consumers' perspectives and opinions of the products [10]. It discusses the many strategies and tactics utilized in ABSA, emphasizing the move toward AI-based deep learning and machine learning approaches to increase the efficacy of ABSA models. The article compares and highlights shortcomings in both methodologies by looking at newly published ABSA approaches based on ML and DL. It highlights the difficulties that the present ABSA models confront and offers recommendations for enhancing the effectiveness and accuracy of ABSA systems.

Techniques Used in ABSA

Manual methods were used in the past to extract features from data. The sentiment lexicon and bag of words were employed to complete the categorization job. The content of sentiment documents was entirely disregarded by the old approaches for recognizing the sentiments. They increased target-based sentiment analysis's accuracy. A rule-based strategy for identifying aspects from sentences and statistical methods forextraction were employed in certain ways. It was suggested to use the Max Ent-LDA model to recognize and detect the elements of opinionated phrases. These models' shortcomings include time consumption, an increase in data amount, and performance degradation from labeled data.

Since the development of artificial intelligence, the steps involved in sentiment analysis have included gathering data, pre-processing, feature extraction, selection, and categorization. Data processing involves the use of NLP algorithms. To extract the aspect from sentences, SVM is utilized. There are four methods for classifying sentiment: CRF, DT, NB, and KNN. It is possible to extract features based on an aspect using maximum entropy, NB, SVM, and RF. The following are ML algorithms' drawbacks.

- The performance would naturally decline as the amount of data increased.
- The machine learning algorithm is incapable of self-learning. They gain knowledge from training data and use that knowledge to make decision-making.
- They are extremely sensitive to data; even a tiny alteration can result in a significant variance in the results.
- Deals with issues such as scaling, transformation, overfitting, etc.

Deep learning is a subset of machine learning models that use deep neural networks to solve learning problems. The overall quantity of input and output layers found in the depth of learning is determined by the network. More pertinent and helpful features are pulled from the remaining deep layers of the DL model as learning progresses, starting with the extraction of abstract features at the beginning stages. These models use several word vectors, such as word2vec to treat basic input text as embedding words. One of the main benefits of utilizing the DL model is its ability to extract features from the data independently, something that ML algorithms could not do. Another benefit of DL is that, in ML-based approaches, they make informed decisions by learning and employing their acquired knowledge to make decisions intelligently from the provided facts, and judgments are subsequently based on this knowledge. While both deep learning and machine learning techniques are forms of artificial intelligence, the primary motivation for converting to DL approaches is their capacity to handle large datasets with high accuracy. But after carefully reading the literature, it is found that most studies have employed CNN and RNN variations in the aspect-based sentiment analysis approach, such as LSTM and BI-LSTM.

Table 1. Comparison of ML models, applications and effectiveness.

Type	Algorithm	Performance	Finding
	Normative patterns in sequence PSO and Google Distances [11]	Obtains favourable outcomes for identifying both explicit and implicit elements	This method is comparable to rule-based architecture rather than commonsense knowledge and dependency [11]
	Unsupervised algorithms	Enhanced rate of classification [12]	describes an unsupervised aspect-based sentiment analysis technique that finds the characteristics and sentiments of the target entity [12].
	SVM	Better in Performance	developed a sentiment analysis technique based on SVM [13].
Machine Learning	DT, NB, KNN, and CRF [14]	DT is best	The model illustrates the effectiveness of ABSA in news content

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	ML and data mining-based model for predicting sentiment	81.24% accuracy	On the twitter dataset, the Naïve Bayes classifier algorithm yielded the best results, with an accuracy rate of 81.1% [15].
	unsupervised methods	enhanced performance	ABSA clustering of words. Languages become better. Only HPS managed a significant portion of the Czech morphology [16]. All four of the ABSA subtasks were enhanced by GloVe, CBOW, and Czech stemming recent discoveries in Czech.
	CNN, Bi LSTM and CRF [18]	specific elements for numerous languages	suggested a model for French performance. As seen with English, CLC is linguistically flexible [17]. The suggested model concurrently detected traits and sentiment, so taking advantage of the relationship between the two.
	Bidirectional encoder Representation from Transformers (BERT) [18]	Efficiency with the various ABSA databases	Aspect-level sentiment analysis was enhanced by MAMN. [18] Compared to Word2vec and Glove, pre-trained BERT initializes word embeddings more accurately. Concealed sentence representations were produced by attention.
	Joint attention-based LSTM (JATLSTM) [19]	Effective with standard databases	sentiment analysis at the aspect level with a combined attention LSTM network (JAT~LSTM) integrates sentiment and aspect attention. Benchmark datasets demonstrate that the proposed technique outperforms the state-of-the-art [19].
Deep Learning	LSTM, CNN, and BiLSTM [20] as well as GRU models	an increase in accuracy of 5 to 20%	A proposed aspect-based sentiment analysis model is included in the ABSA models. A deep neural network design for ensemble learning was suggested. Deep learning models including CNN, LSTM, BiLSTM, and GRU were created and trained using the recommended approach [20]. Base classifier results were integrated in a logistic regression model to create a meta-learner. In terms of precision, the suggested approach beats the baseline method by 20%.
	LSTM combined with adaptive PSO [21]	surpasses conventional models in performance	Skip gramme characteristics are extracted by word embedding. Skip-gram RNN, LSTMWord-for-word Vector encoding is more precise and requires less memory [21]. In the absence of optimization, LSTM functions well. The performance of LSTM weight parameters was optimized by APSO. The accuracy and computational complexity of LSTM neural network weight parameters chosen by APSO are enhanced [21]. The accuracy rates for Amazon were 96.8%, travel advisors were 97.8%, demonetization was 93.2%, and book reviews were 95.2%

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	RNN, LSTM and CNN [22]	85% accuracy	It provided a Hindi lexicon-based dictionary and a domain-specific sentiment dictionary. sentiment analysis (NRC Emotion Lexicon, Hindi SentiWordNet). Using a CNN, RNN, and LSM, 23,767 Hindi tweets were categorized as positive, negative, or neutral. The accuracy of the CNN approach was 85% [22].
	graph attention n-based CNN	F-Score of 88.16% [23]	For implicit sentiment analysis, a graph attention neural network (GACNN) model was presented. [23] The lack of a particular emotional language in implicit sentiment analysis makes it more difficult to convey mood and extract sentiment features. Important words were prioritized and multiple attention was distinguished using orthogonal and score attention restrictions. The impact of external knowledge on implicit sentiment analysis was not investigated in this study.

Conclusion

We examined the two types of current ABSA approaches ML-based ABSA and DL-based ABSA in order to comprehend the idea of ABSA. Based on the review, it is determined that SVM, an ML-based binary classifier, because tree algorithms like DT, RF, and NB are straightforward and simple to apply, researchers have primarily employed them in their work to analyze characteristics in words, phrases, or remarks. SVM's inability to function properly when there are several aspects in the text is one of its main disadvantages, whereas tree-based algorithms can become unstable due to little changes in the data. Furthermore, ML algorithms frequently lose a lot of data during the pre-processing and feature extraction stages and were unable to handle the complex and massive datasets. Researchers turned to DL-based methods to get around these problems. In their work, a significant number of experts employed CNN, RNN-based LSTM, and Bi-LSTM. because of their capacity to automatically extract features from text. Although deep learning techniques are capable of processing enormous datasets with efficiency, their high error susceptibility and massive training data requirements have a negative impact on the accuracy of textual aspect detection. Ultimately, it can be said that using hybrid deep learning techniques to common datasets can increase the precision of emotion detection. The problems that follow demonstrate that sentiment analysis is still an area of growing research interest.

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