A Review on Machine Learning and Deep Learning Models for Sentiment Analysis

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Abstract Opinion Mining and sentiment analysis of big data has been seen as an active area of research lately. It has a wide range of applications in information systems, including classifying reviews, summarizing review and other real time applications. There are promising possibilities to use sentiment analysis in real time business models. This work analyses the use of sentiment analysis for analysing customer reviews. Customer reviews are a valuable source of feedback for businesses. However, manually analyzing a large volume of reviews can be time-consuming. Sentiment analysis automates this process, providing a quick and scalable way to comprehend the overall sentiment expressed by customers. Sentiment analysis helps businesses identify positive customer experiences. By recognizing positive sentiments in reviews, companies can pinpoint what aspects of their products or services are well-received by customers. This information is crucial for reinforcing and promoting positive features. This paper presents a review on machine learning based sentiment analysis techniques and their salient features.

Keywords: Data Mining, Customer Review, Sentiment Analysis, Machine Learning, Bayesian Classifier, Classification Accuracy.

1. Introduction

Customer sentiment analysis relies heavily on machine learning, which gives companies an effective tool for understanding and reacting to customer feedback. In a day of digital communication and information overload, it is critical to comprehend the feelings that customers are expressing. This paper examines the several factors that make machine learning essential for efficient customer sentiment analysis [1].
The sentiment extraction of users from large and complex data sets is however daunting. This is to be ensured that the context (semantics) is to be taken into account prior to reaching conclusions and implicit meaning has to be inferred correctly. Moreover accurate data pre-processing needs to be imposed in order to segregate the useful information from the raw data. Since user sentiments have a critical impact on several parameters and domains, hence sentiment analysis is critically important. While several data sources are available on the internet to be mined, yet a judicious use of web mining is to be done prior to any system design model is to be used. The critical factor is also the feature selection from the raw data to be included in the analysis of the data as a whole. Machine learning's ability to manage enormous amounts of consumer input is one of the main reasons it is crucial for sentiment analysis. Businesses now receive a dizzying amount of data from a variety of sources, including surveys, emails, social media, and online reviews. This scale is beyond the capabilities of traditional methodologies; in contrast, machine learning models process massive datasets effectively, allowing organisations to analyse feelings more broadly [2].

Sentiment analysis faces a great deal of difficulty due to the complexity of human language. Natural language processing (NLP) in particular, which is a subset of machine learning, is excellent at identifying intricate patterns, contextual subtleties, and minute differences in consumer reactions. Beyond crude positive or negative classifications, this capacity to interpret linguistic nuances enables a more precise and sophisticated sentiment analysis. Consumer perceptions are subject to alter due to new product offers, shifting trends, and outside events. By continuously learning from fresh data, machine learning models demonstrate adaptability. This flexibility guarantees that sentiment research is current and representative of the customer landscape, allowing organisations to react quickly to shifting emotions and make well-informed decisions. Personalised sentiment analysis catered to certain sectors and circumstances is made possible by machine learning. Businesses can tailor sentiment analysis tools to meet their specific needs by training models on language specific to their industry. By taking a customised approach, sentiment research becomes more accurate and companies pay attention to the things that are most important to their customers [3].

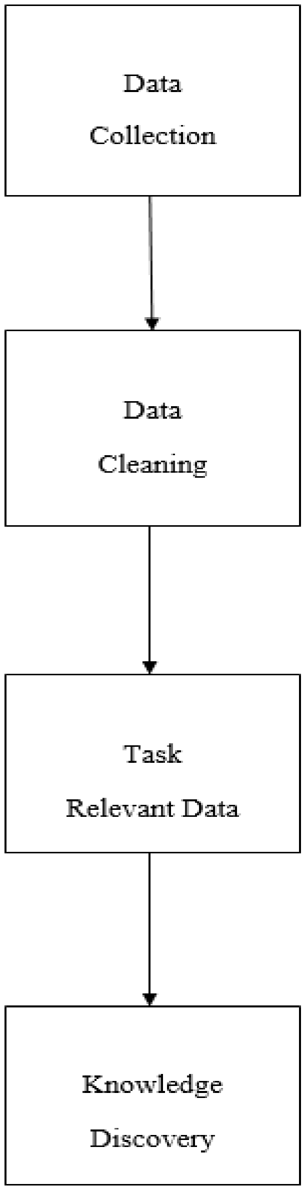

Fig.1 Steps for Sentiment Analysis

Automatic feature extraction, key phrase recognition, and word associations with positive or negative sentiments are areas where machine learning shines. This feature gives companies the ability to identify particular features of goods or services that affect how customers perceive them, giving them insightful information for future development.

II. Literature Review

The literature survey of various scholars related to the review is as follows:-
Zhao et al. [1] proposed a multimodal sentiment analysis method based on the multimodal sentiment analysis method that can obtain more sentimental information sources and help people make better decisions. The experimental results in this paper show that the highest recognition rates of CNN-SVM, 93.5%, respectively.
Dhyani et al. in [2] author proposed a novel intuitionistic fuzzy inference system (IFIS) for the sentiment analysis. The research paper does the sentiment analysis of using tweets and predicts the personality trait characteristics of the tweeting individual through proposed IFIS. Twitter data was analyzed using Natural Language Processing Toolkit (NLTK) through TextBlob in Google Colaboratory for their subjectivity and polarity to predict the score of their positivity using proposed novel IFIS Vohra et al. [3] proposed a model uses multiple convolution and max pooling layers, dropout operation, and dense layers with ReLU and sigmoid activations to achieve remarkable results on our dataset. Further, the performance of our model is compared with some standard classifiers like Support Vector Machine (SVM), Naive Bayes, Decision Tree, and Random Forest. From the results, it is observed that on the given dataset, the proposed CNN with FastText word embeddings outperforms other classifiers with an accuracy of 0.925969. As a result of this classification, 54.41% of the tweets are found to show affirmation, 24.50% show a negative disposition, and 21.09% have neutral sentiments towards.
Phan et al. [4] proposed a model which includes the following steps: First, words in sentences are converted vectors using BERT. Second, the contextualized word representations are created based on BiLSTM over word vectors. Third, significant features are extracted and represented using the GCN model with multiple convolutional layers over the contextualized word representations.

Finally, the aspect-level sentiments are classified using the CNN model over the feature vectors. Experiments on three benchmark datasets illustrate that our proposed model has improved the performance of the previous context-based GCN methods for ALSA.

Obiedat et al. [5] proposed a hybrid approach by combining the Support Vector Machine (SVM) algorithm with Particle Swarm Optimization (PSO) and different oversampling techniques to handle the imbalanced data problem. SVM is applied as a machine learning classification technique to predict the sentiments of reviews by optimizing the dataset, which contains different reviews of several restaurants in Jordan. Data were collected from Jeeran, a well-known social network for Arabic reviews. A PSO technique is used to optimize the weights of the features.

Vashishtha et al.

Vashishth et al. [6] proposed MultiLexANFIS which is an adaptive neuro-fuzzy inference system (ANFIS) that incorporates inputs from multiple lexicons to perform sentiment analysis of social media posts. Authors classify tweets into two classes: neutral and non-neutral; the latter class includes both positive and negative polarity. This type of classification will be considered for applications that aim to test the neutrality of content posted by the users in social media platforms. In the proposed model, features are extracted by integrating natural language processing with fuzzy logic; hence, it is able to deal with the fuzziness of natural language in a very efficient and automatic manner.

Saha et al. [7] employed different machine learning algorithms for sentiment analysis. The algorithms such as Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Multilayer Perceptron (MP) on the linguistic features were employed. Authors have determined the precision, recall, F-measure, accuracy, ROC values for each of the classifiers. Among the classifiers Random Forest has outperformed others showing 60.54% correctly classified instance. We believe such sentiment analysis on special category of texts may lead to further investigation in natural language understandings.

Estrada et al. [8] presented a comparison among several sentiment analysis classifiers using three different techniques – machine learning, deep learning, and an evolutionary approach called EvoMSA – for the classification of educational opinions in an Intelligent Learning Environment called ILE-Java. Authors develop two corpora of expressions into the programming languages domain, which reflect the emotional state of students regarding teachers, exams, homework, and academic projects, among others. A corpus called sentiTEXT has polarity (positive and negative) labels, while a corpus called eduSERE has positive and negative learning-centered emotions (engaged, excited, bored, and frustrated) labels.

Rahat et al. [9] proposed a method in which authors have preprocessed the dataset to convert unstructured airline review into structured review form. After that, we convert structured review into a numerical value. We have to preprocess the data before using it. Stop word removal, @ removal, Hashtag removal, POS tagging, calculating sentiment score have done in preprocessing part. Then an algorithm has been applied to classify the opinion as either it is positive or negative. In this research paper, we will briefly discuss supervised machine learning. Support vector machine as well as Naïve Bayes algorithm and compares their overall accuracy, precession, recall value. The result shows that in the case of airline reviews Support vector machine gave way better result than Naïve Bayes algorithm.

Hasanli et al. [10] developed a roadmap of sentiment analysis of twits in Azerbaijani language. The principles of collecting, cleaning and annotating of twits for Azerbaijani language are described. Machine learning algorithms, such as Linear regression, Naïve Bayes and SVM applied to detect sentiment polarity of text based on bag of word models. Our suggested approach for data processing and classification can be easily adapted and applied to other Turkish language. Achieved results from different machine learning algorithm have been compared and defined optimal parameters for the classification of twits.

A summary of literature review is presented next.

Table 1. Summary of Previous Work

Reference	Approach	Results and Findings
Zhao [1]	CNN-SVM	Convolutional Neural Network- Support Vector Machine hybrid model used for sentiment classification. The CNN-SVM model used to estimate sentiment polarity from social media texts. Accuracy Percentage: 93%.
Dhyani [2]	Intuitionistic Fuzzy Inference System (IFIS)	Intuitionistic Fuzzy Inference System (IFIS) System used for sentiment analysis. RMSE Value of 0.3 obtained for model.
Vohra [3]	CNN	Convolutional Neural Network (CNN) model used for sentiment analysis which attained accuracy of 92.6%
Phan [4]	Graph Convolutional Neural Networks (GCN)	The Graph Convolutional Neural Networks (GCN) used for sentiment classification which obtained accuracy of 85.2%
Obeidat [5]	PSO-SVM	The particle swarm optimization (PSO) combined with Support Vector Machine model for sentiment analysis. Accuracy of 89% obtained.

III. Existing Methodology

Sentiment Analysis using Machine Learning

Machine learning algorithms are often very helpful in conveying and prioritizing whether a document represents positive, neutral or negative emotions. Machine learning is grouped into two types of extensions such as unsupervised algorithms. The supervised algorithm uses a labeled dataset where each training document is written with positive emotions. While, unsupervised readings include raw data where the text is not written and positive emotions. The commonly used machine learning models used are [11]

Convolutional Neural Network (CNN): A CNN's basic architecture is made up of layers that handle incoming data in a hierarchical fashion. The main parts are fully connected layers, pooling layers, and convolutional layers. By using filters or kernels to the input data, convolutional layers extract features by identifying local patterns and details. In order for CNNs to learn hierarchical representations from unprocessed input, these layers are essential. Convolutional layers carry out the vital function of extracting features. Sliding a filter over the input data and calculating the dot product at each place comprise the convolution procedure. Activation functions add non-linearity to the network after the convolutional process. ReLU (Rectified Linear Unit), a popular activation function, introduces non-linearities by thresholding the output, allowing the model to learn more intricate feature correlations [12].

Support Vector Machine (SVM): One potent class of machine learning techniques used for both regression and classification applications is Support Vector Machines (SVMs). They have become well-known for their reliable operation and adaptability in a variety of fields. The goal behind Support Vector Machines (SVMs) is to identify the optimal hyperplane for separating data points into distinct groups. By acting as the decision boundary, this hyperplane maximises the margin between the classes. SVMs work well in high-dimensional environments, where they are useful for jobs requiring a large number of input features. SVMs are unique in that they prioritise maximising the gap between each class's nearest data points and the decision border. The distance between the closest data point and the hyperplane is known as the margin [13] .

Hyperplane in SVM: The data points that are closest to the decision boundary or hyperplane are known as support vectors. In order to define the margin and, by extension, the decision boundary, these points are essential. These support vectors are what give support vector machines (SVMs) their moniker because they help find the best possible hyperplane. When data cannot be separated linearly, SVMs use the kernel trick to convert the input space into a higher-dimensional space. SVMs can handle complex decision boundaries with ease thanks to this transformation, which allows them to locate a hyperplane in the modified space. Polynomial, sigmoid, and radial basis function (RBF) are examples of common kernel functions. Optimising a cost function that takes into account the margin size and classification accuracy is necessary for training a support vector machine. The goal of the optimisation method is to identify the ideal hyperplane [14].

Bayesian Approach

Probabilistic graphical models known as Bayesian Networks, or BayesNets, use Bayesian probability to depict and infer relationships between variables. Regarding sentiment classification, BayesNets provide a logical and comprehensible method. This paper explores the use of BayesNets in sentiment classification, emphasising the advantages and drawbacks of this method for identifying emotional overtones in textual data. Determining the sentiment expressed in a text and classifying it as good, negative, or neutral is known as sentiment classification. A probabilistic modelling framework that is well-suited to the ambiguity contained in language is offered by BayesNets, which enables the capture of dependencies between words or phrases and the nuanced depiction of sentiment [15].

With directed acyclic graphs (DAGs), Bayesian networks depict conditional dependencies between variables. Nodes in the network can represent words or features in the context of sentiment categorization, while edges show conditional dependencies. Because of this structure, BayesNets can accurately represent how the presence or absence of specific words affects the likelihood of a given feeling. In a BayesNet, each node has associated probabilities that indicate the chance that a variable will take on a specific value based on the values of its parent nodes. These probabilities, which indicate the possibility of noticing particular words or features given the sentiment indicated in the text, can be learned from training data in sentiment classification.

Sentiment analysis requires the ability to handle uncertainty and variability, which BayesNets naturally provide. It's common for language to be vague, and there are many methods to convey feelings. Because BayesNets incorporate prior probabilities and adapt their beliefs based on mounting information, they facilitate the modelling of uncertainty. They are therefore capable of managing a wide range of language manifestations of emotion. Prior knowledge can be included with BayesNets, which is especially helpful for sentiment categorization. An enhanced and contextually aware sentiment analysis can be achieved by encoding into the network prior knowledge about words or phrases that strongly suggest a particular sentiment [16].

The performance parameters used for evaluation of classification are [17]:

$$\boldsymbol{Accuracy = \frac{TP+TN}{TP+TN+FP+FN}} \quad (1)$$

$$\boldsymbol{Sensitivity\ or\ Recall = \frac{TP}{TP+FN}} \quad (2)$$

$$\boldsymbol{Specificity = \frac{TN}{TN+FP}} \quad (3)$$

Here,
TP, TN, FP and FN denote true positive, true negative, false positive and false negative respectively.

Conclusion:

In conclusion, Sentiment analysis has become a crucial tool for commercial purposes, offering valuable insights into user activities and choices. By employing sentiment analyzers, various methods and algorithms within Natural Language Processing (NLP) are utilized for a comprehensive understanding. This research conducts an extensive review of diverse datasets and research works employing different machine learning techniques for sentiment analysis. Sentiment analysis using machine learning has proven to be a powerful and versatile tool for extracting valuable insights from textual data. The reviewed studies showcased a diverse range of techniques, from traditional methods like Random Forest and Word2Vec to advanced approaches such as Recurrent Neural Networks (RNN). These techniques have demonstrated high accuracy in discerning sentiment across various domains. The future holds promise for continued advancements, particularly in the realm of video sentiment analysis, where the extraction of features from frames and the application of machine learning algorithms are poised to play a pivotal role. Overall, the research underscores the significance of machine learning in unraveling sentiment patterns, contributing to a deeper understanding of user sentiments in diverse applications and domains.

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