Comparison of Sentiment Analysis on Online Product Reviews Using Optimised RNN-LSTM with Support Vector Machine

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Abstract

Using sentiment analysis, opinion mining examines the emotional tone and polarity of text (positive, neutral, or negative), as well as the sentiment polarity of text. With the rise of online information, sentiment analysis of customer evaluations has become a hot topic among machine learning researchers. Review texts for products online express a wide range of feelings and thoughts. By using natural language processing tools on the Internet, it will be possible for natural language processors to extract useful information from online reviews by performing sentiment analysis. It assigns polarity to a positive or negative entity or item. From the product reviews collected on Amazon, we conduct a Sentiment Analysis. As a result of asymmetrical weighting, we feed our feature words to support vector machine classifiers as well as Recurrent Neural Networks-Long Short Term Memory (RNN-LSTM)-optimised methods for determining the sentiment direction of reviews.

Keywords

Sentiment Analysis, Natural Language Processing, Support Vector Machine, Recurrent Neural Network - Long Short-Term Memory.

Introduction

Due to the rapid development of Internet technology, online shopping has become an extremely popular means of ordering goods and availing of other services. Online shopping is becoming increasingly popular as a means for people to buy and consume goods. Through analyzing online reviews, organizations can attract customers by guiding their purchasing decisions, as well as get feedback on their products and predict the outcome of major events, such as elections. The polarity of emotions expressed in financial reviews can be used to predict the future market prices, stock prices, and earnings of companies. Customer satisfaction can be improved by analyzing the sentiment of reviews on e-commerce sites. Using polarity analysis to analyze emotion expression in financial texts, Devitt et al., (2015) identified just that.

A company can better understand the public sentiment towards their brand, product, or services by using sentiment analysis, a textual mining method that finds and collects subjective information from the source material. However, most social media analysis focuses on sentiment analysis and count-based statistics. Although it does not categorize words, it analyzes incoming messages and indicates their positivity, negativity, or neutrality (Suad et al, 2017). A variety of methods can be employed in sentiment analysis. However, the selection of the right words to use as features is a crucial step.

Today, many documents are available on the internet containing a great deal of information. The effort to categorize these documents for the benefit of users has led researchers to investigate how automatic text categorization can be achieved. The vast majority of these projects focus on topical categorization, in which documents are categorized according to their subject matter. Recently, online discussion groups and review sites have developed rapidly where one of the most crucial characteristics of posted articles is sentiments.

An Amazon.com review is classified by using an optimised Recurrent Neural Network (RNN-LSTM) and support vector machine classifier after weighting word features asymmetrically. Deep learning neural networks called RNNs (Recurrent Neural networks) learn data sequences and are primarily used to classify textual data. RNNs are in trouble with vanishing gradients when working with long sequences of data. With LSTM neural networks (S. Hochreiter & J. Schmidhuber, 1997), the problem can be solved. A variety of real-life applications have already shown the effectiveness of these networks, including speech recognition (Graves et al, 2013), image captioning (Vinyals et al., 2018), and music composition (D. Eck & J. Schmidhuber, 2002). The sentiment of a review is highly dependent on its contextual setting. The quality and satisfaction of customer service can be improved by offering examples of customer evaluations for firms that use e-commerce platforms.

During the first section of this paper, an introductory part is provided; during the second section, a literature review is presented. Section 3 gives a short description for the concept Sentiment Analysis System and Natural Language Processing, Section 4 depict the methodology and the SVM and RNN-LTSM classifiers, Section 5 deals with the evaluation and the measures used for comparing the two classifiers. Section 6 gives the result of the study. Section 7 deals with the challenges in Sentiment Analysis. Section 8 gives the conclusion for the work.

Studies related to sentiment analysis have been published more frequently in recent years. There have been more initiatives focused on sentiment in textual resources recently. Those studies are taken into account in the current research paper. In addition to sentiment analysis, other research areas have been examined. Opinion mining is another term for this. This was offered as a collection of textual content. People's opinions, assessments, attitudes, and feelings for entities are all considered in such studies.

Literature Review

Various levels of sentiment analysis can be applied, including at the document, phrase, and sentence level. Out of these levels, you can analyze positive, negative, or neutral meanings based on their content. We previously assigned polarity to words and phrases according to the extent of their positive or negative connotations. In many circumstances, this prior categorisation is useful, but when contextual polarity is involved, the meaning acquired from positive or negative polarity can be completely different.

This study incorporated LSTM into CNN’s pooling layer to find a rumour based on consumer opinion. Sheng et al. (2020) did this with convolution neural networks and LSTMs (CNN-LSTM). Furthermore, we have incorporated perception into the rumour detection model. Zhang et al. (2016) derived compositional sentiment rules to calculate textual sentiment. As a result, the system eliminated the need for machine learning.

By recursively learning neural networks, Socher et al. (2013) have developed a model to model semantic compositionality along a sentiment treebank. Using Stanford sentiment tree data, they achieve state-of-the-art performance on binary sentiment classification. The paper in which Kim (2014) describes the creation of a simple and powerful Convolutional Neural Network (CNN) for sentiment analysis performed remarkably well across the different datasets.

Using Lexicon-enhanced LSTM algorithms, he studied three English datasets: IMDB, Yelp 2013, MR, as well as two Chinese datasets: NB4000 and Book4000. The accuracy of 89%, 60.6%, 79.9%, 93% and 96% of the proposed method was higher than that of ALE-LSTM and WALE-LSTM.

Zhang et al. (2019) presented a study illustrating that the accuracy of a stock closing forecast is determined by using LSTM and sentiment analysis. This study was the first to consider investor perceptions, which resulted in improved accuracy. Ouyang et al. (2015) implemented sentiment analysis using a seven-layer convolutional neural network architecture.

There have been several deep-learning models combined to improve sentiment analysis. For example, Zhang et al. (2019) developed a Grid Search (GS) model using LSTM-CNN to predict sentiment from Amazon movie reviews and IMDB movie reviews. In their suggested study, the authors used a grid-search strategy and compared their model to many baseline algorithms such as CNN, LSTM, CNN–LSTM, and others, with findings showing that their model surpassed the baselines with an overall accuracy of 96 %. Ouyang et al. (2015) used Amazon reviews in a similar study, in which topic modelling was done first with Fuzzy C-means before CNN was used to classify opinions.

To develop a Target-dependent Convolutional Neural Network (TCNN), Hyun et al. (2021) measured the distance between a target word and the surrounding words. Because words have various effects on the emotional polarity of sentences, attention mechanisms emerge. Ma et al. (2019) presented an extended LSTM termed Sentic LSTM to incorporate the dominant and recessive aspects in the phrase. A separate output gate is included in the model unit for inputting token level memory and concept level input.

Akyol et al. (2019) have developed a Sentiment Analysis-based Optimization Algorithm as well as a Whale Optimization model. A conventional programming optimization strategy was used by Yang et al. (2018) to evaluate the sentiment, or quality, of the feedback between tweets and news. Keshavarz et al. (2020) created a sentimental analysis model based on a genetic algorithm. Six distinct datasets were employed in the tests, and the results were more accurate.

Sentiment Analysis System

Among the primary objectives of Natural Language Processing (NLP) is sentiment analysis. NLP combines the disciplines of Artificial Intelligence, linguistics, and computer science into one discipline. The goal is for computers to interpret or "understand" natural language in order to do tasks that are similar to those performed by humans, such as language translation and question answering. It has a wide range of applications, including analysing political opinions on social media, obtaining information from user-generated product reviews, and even designing trading market strategies' sentiment.

People frequently see sentiment as the most important value of the comments expressed on social media. In actuality, emotions give a more comprehensive set of data that influences customer decisions and, in some situations, even dictates them. As a result, NLP for text-based sentiment analysis is incredibly beneficial. Organizations may analyse consumer reactions and respond accordingly using NLP for text analysis combined with a sophisticated social media monitoring strategy to improve customer experience, quickly handle customer complaints, and shift their market position.

Sentiment analysis may help enhance decision-making processes in a variety of industries, including banking and stock markets, digital payment systems, retail, and products, among others, by obtaining user feedback on a certain topic or text (2017). Aspects of sentiment analysis based on textual communication have also been discussed or quantitatively quantified, frequently using a scale of 1 to 5 or 10 points. The use of numerical numbers (or stars) to represent the intensity of one's sentiment is referred to as a sentiment rating (Keshavarz et al., 2017). While machine learning algorithms are commonly used for sentiment analysis, deep learning algorithms have demonstrated promising results in recent years.

Despite its popularity among research scholars, sentiment analysis is primarily used to gauge how people feel about something, and its application in various fields is due to the widespread use of social media.

According to figure 1, as part of the sentiment analysis process, stop words are removed from a dataset. The sentiment identification step then determines what customers are saying about the product and analyzes it according to the feedback. The results are analysed using sentiment analysis (Sharma et al., 2018). An example of the sentiment analysis system is shown in figure 1.

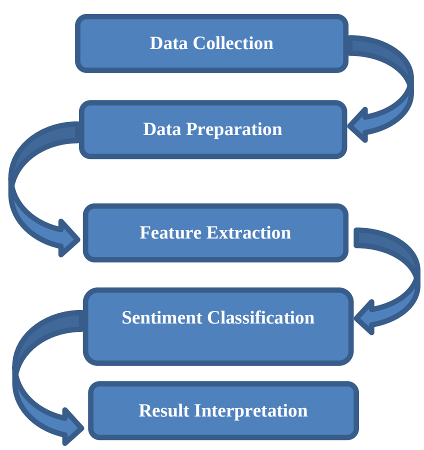

Figure 1 Sentiment Analysis System

1. Data Collection

According to the numerous reviews available on Amazon, it is the second most popular e-commerce site. Unfortunately, the dataset was unlabeled, and so it couldn't be used in a supervised learning model. Finally, our research project relied solely on Amazon product feedback. The customer reviews of various Amazon products were selected as the dataset. The dataset contains 34,000 reviews from customers that are rated on a scale of 1-4 depending on what they think about the product. Data collecting was completed as the first step in the data labelling process. Manual labelling is impractical for a human to do because the dataset contains a high number of reviews. As a result, after the datasets have been preprocessed, the active learner has been used to label them.

2. Data Preparation

Data had already been gathered from assessment records completed by the customer. This evaluation is based on Amazon's product offerings. Approximately 35,000 informational points are encircled by this type of data. Each sample includes the product's kind, name, and written review, as well as the product's rating. Data preparation includes data cleaning, data integration, data transformation and data reduction. Data cleaning helps to identify and remove the data that are incomplete, noisy, and inconsistent from a database. Integration of data across heterogeneous data sources provides a unified view of the data by combining data from multiple sources into one store. By reorganizing or reformatting raw data, data transformation helps data mining retrieve strategic information efficiently and easily. By reducing the volume of data, data reduction helps to save storage space and reduce data storage and analysis costs.

Pre-processing of data involves removing uninformative and noisy sections, such as HTML tags, scripts, and advertisements, to prepare it for classification. Furthermore, many words in the text have little bearing on the overall direction of the document. As a result of keeping these words, the problem becomes one of dimensionality, making it more difficult to categorize since each word in the text is considered a separate dimension. When data is appropriately pre-processed, the goal is to reduce the amount of noise in the text, allowing the classifier to perform a more effective classification and to process the classification process faster, thereby allowing real-time sentiment analysis. Cleaning of text, removing white space, the extension of abbreviations, stemming, removal of stop words, negation handling, and determining the features are all part of the process. The last one is called a transformation.

As part of preprocessing data, three steps are done: tokenization, stopping words removal, and filling in the missing values using the global constant.

a) **Tokenization:** The process involves breaking apart a string sequence into individual elements like words, phrases, symbols, letters, and many others. It is possible to create tokens that create phrases, words, or even complete sentences. During tokenization, many characters are removed, including punctuation marks, which are then used with various applications, such as text mining and parsing.
b) **Removing stop words:** A stop word is any item in a sentence that doesn't contribute to any subdivision in text mining. Using these terms is usually avoided to increase the assessment's accuracy. There are various types of stopwords, which are dependent on the realm, the language, etc. In English, however, there are a few stopwords.
c) **Filling the missing value with global constant:** As part of this stage, the system searches the dataset for missing values. Missing values are then replaced by the appropriate constant to complete the process.

3. Feature Extraction

To represent words mathematically, the sentiment features are identified and the word embedding technique is used. In this study, a hybrid approach of Skip N-Gram model and TFIDF hybrid method is used for feature extraction.

a) **Skip N-Gram model:** A skip-gram is a generalization of n-grams found in computational linguistics, namely language modelling, in which the components (typically words) of the skip-gram are not necessarily consecutive in the text under consideration, but are allowed to leave gaps. A skip-gram can overcome the data sparsity problem that is associated with n-gram analysis. In terms of computer security, skip-grams are more robust than n-grams in resisting attack. N-grams are closed sequences of tokens w1 … wn that occur consecutively. K-skip-n-grams are close-range sequences in which the components are close to each other.
b) **TFIDF hybrid method:** The TF-IDF is a means of measuring the mathematical significance of words in documents. Multiplying the TF and IDF values yields the TF-IDF value. As the name implies, “Term Frequency” (Term Frequency) refers to the number of target terms within a document compared with the total number of terms within it. A logarithm of the ratio of documents with the targeted term and the total number of documents is used to calculate the initial IDF values. There is no concern about how many times the term appears in the document at this point.

4. Sentiment Classification

These areas of text mining include Opinion Mining and Sentiment Analysis, which involve generating interesting patterns and information from unstructured script materials. Text mining and sentiment analysis are similar in appearance, but they differ in the following ways. The binary polarity classification Sentiment Classification (SC) works with a relatively small number of classes (Colón-Ruiz et al., 2020). When compared to text auto-classification, sentiment classification is a straightforward task. Opinion mining, on the other hand, performs a variety of additional tasks in addition to emotion polarity identification. Here we use SVM and RNN-LSTM for the classification and we compare the results obtained. The sections that follow give details about SVM and RNN-LSTM.

5. Result Interpretation

Deep learning algorithms use a large amount of unstructured data to extract meaningful information from complex, unstructured data sets. They can adapt quickly to changing information and produce cutting-edge forecast results. They are, in fact, complex models with multiple layers. The classification results from the SVM classifier and RNN-LSTM classifier is compared using measures like Accuracy, F-measure, Precision, Recall, Sensitivity and Specificity which is discussed in the following sections.

Methodology

The proposal discusses a technique that can be used to analyze the relationship between online reviews and performance revenue by using sentiment analysis and machine learning techniques. Based on the online product reviews, the techniques predict which products will be collected, and analyzes how much of an impact the reviews have on the collection. This study uses product reviews collected by Amazon, which has over 200 million unique visitors monthly in the U.S., accounted for 37% of all online retail sales in 2020, and dominated the e-commerce industry in 2016 with $385 billion in net sales. Consumers are increasingly relying on one of the most potent e-commerce tools: customer reviews, as Amazon continues to develop at a breakneck pace. After the data collection, the dataset undergoes feature extraction. Features are extracted using Skip N-Gram and TFIDF methods. We are comparing the results from two classifiers, that is Support Vector Machine and RNN with LSTM classifiers are applied on the data and finally accuracy of the two classifiers are compared. The methodology of the system is as shown below in fig 2. Consumers are posting product reviews directly on product pages instead of using traditional brick and mortar retail stores. As a result, reviews are becoming increasingly important as brick and mortar retail stores transition to online shopping. As a result of the vast amount of consumer reviews, we can see how the market reacts to a particular product. We will attempt to predict the sentiment with the help of machine learning.

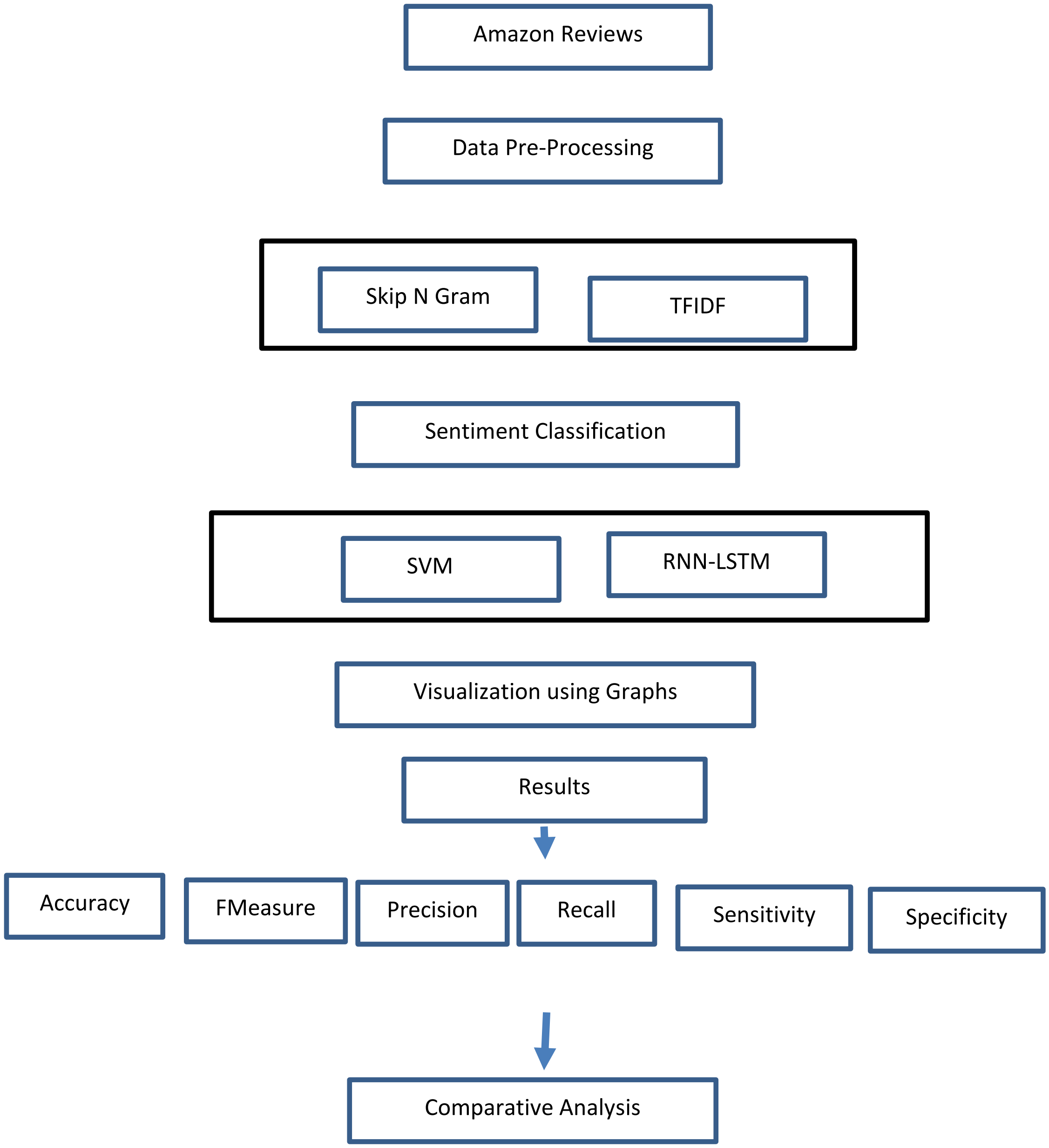

Figure 2 Methodology of Sentiment Analysis

1. Classification Using Support Vector Machine Classifier

Supervised Learning algorithms are popular for Classification as well as Regression, using Support Vector Machines to create hyperplanes. In SVMs, extreme points help to create the hyperplane. Thus, the algorithm is called Support Vector Machine and the extreme points are called support vectors.

Each data element in your database consists of a point in n-dimensional space (n being the number of features) whose coordinates represent its value. To solve classification and regression problems, the support vector machine algorithm will be used to find the hyperplane that distinguishes clearly between the two classes. Several fields have used it (bioinformatics, information retrieval, computer vision, finance, etc.). The main reasons for the popularity of SVMs include their ability to handle a large amount of data, the small number of hyperparameters, their theoretical guarantees, and their excellent performance in practice.

An SVM can be applied to linear as well as non-linear data. If the data is linearly separated, it will locate the best separating boundary, which is a separating boundary separating data between categories. A nonlinear mapping algorithm is applied in cases where linear separability is not possible (U Ravi Babu, 2017). It reduces the dimensionality of the dataset so that two parts of the data can be effectively separated (Kishori et al., 2015). Po-Wei Liang et al., (2013) designed an algorithm called an "opinion miner" that investigated and detected the sentiments expressed in social media posts automatically.

2. Classification Using Optimised Rnn-Lstm Classifier

Traditionally, neural networks are assumed to be independent of one another. However, this can pose problems for tasks like guessing the next word in a sentence (Bose et al., 2018). Depending on the previous word or sequence of words, the following word will be determined. RNNs come in handy in these situations since they excel at gathering sequential data. The architecture of RNNs contains loops that enable them to transmit information gathered from previous inputs to new inputs as they process those inputs. The Long Short Term Memory (LSTM) was invented by Hocheriter and Schmindhuber in 1997. LSTM networks are RNN types that are capable of recognizing long-term dependencies. In today's world, they are used primarily for activities such as speech recognition and text classification. We employ optimised LSTM RNNs for our neural network technique because they perform better than typical RNNs at learning relationships in sequential data. Gradients from the goal function will disappear or burst after multiplying the weights of the network multiple times, which leads to problems while using RNNs for cognitive tasks (Salleb et al. 2000). Because of this, simple RNNs are rarely used in NLP applications like text classification (Wilson et al., 2005; Richa et al., 2020). In this case, we can use another RNN model, such as the LSTM model, from the RNN family. The availability of input gates, forget gates, and output gates, which govern the flow of information across the network, makes LSTMs better adapted to this task.

Evaluation

Precision, recall, and F-measure, Sensitivity, Specificity, Accuracy are the performance metrics used to assess the categorization outcomes. The values of true positive (TP), false positive (FP), true negative (TN), and false-negative (FN) assigned classes on empirical are used to calculate those metrics. As in other studies, this paper uses sensitivity, specificity, accuracy, precision, recall, and F1 score as metrics of model evaluation. Following are the calculation parameters.

True Positives (TP) - These are the correctly predicted positive values which mean that the value of the actual class is yes and the value of the predicted class is also yes.
True Negatives (TN) - These are the correctly predicted negative values which mean that the value of the actual class is no and value of the predicted class is also no.
False Positives (FP) - When the actual class is no and the predicted class is yes.
False Negatives (FN) - When the actual class is yes but the predicted class is no.
Accuracy - The most intuitive measure of performance is accuracy, which is simply the percentage of correctly predicted observations to the total observations.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \times 100\% \qquad (1)$$

Precision - Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \qquad (2)$$

Recall (Sensitivity) - Recall is the ratio of correctly predicted positive observations to all observations in actual class - yes.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

F1 score - F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account.

$$F - measure = \frac{2*Precision*Recall}{Precision+Recall} \qquad (4)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \qquad (5)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \qquad (6)$$

Result

Sentiment analysis uses the following features for classification: Accuracy, Precision, Recall, F-Measure, Sensitivity, Specificity, which are multiplied by the positivity and negativity calculated from reviews as measured by the proposed hybrid approach. Classifier performance is determined by the following formulas: Report of the true positive instances (Sobana et al., 2021; Socher et al., 2011). To put it another way, it is the ratio between how many positive instances were classified correctly and how many should have been classified correctly. The TP Rates and the FP rates, which have a symmetrical arrangement to the previous definition, may be used to construct a matrix of confusion for a given class. By calculating the TP Rate and FP Rate, it is possible to reconstruct the matrix of confusion. Precision is defined as the difference between the number of true positives and the total number of true positives plus false positives. If a value of 1 is present, all positive examples have been identified. The recall is calculated by selecting the correct items from the list. In other words, when the recall is 1, all the positive instances were found. The accuracy index is proportional to how many positive instances were correctly classified, while the error-index measures incorrectly classified instances.

Table 1 Performance result obtained from SVM classifier

Precision	Recall	F- measure	Accuracy	Sensitivity	Specificity
91.99	91.27	91.15	91.36	91.27	91.66

Table 2 Performance result obtained from Optimised RNN-LTSM classifier

Precision	Recall	F- measure	Accuracy	Sensitivity	Specificity
93.57	93.15	93.57	93.26	93.15	93.78

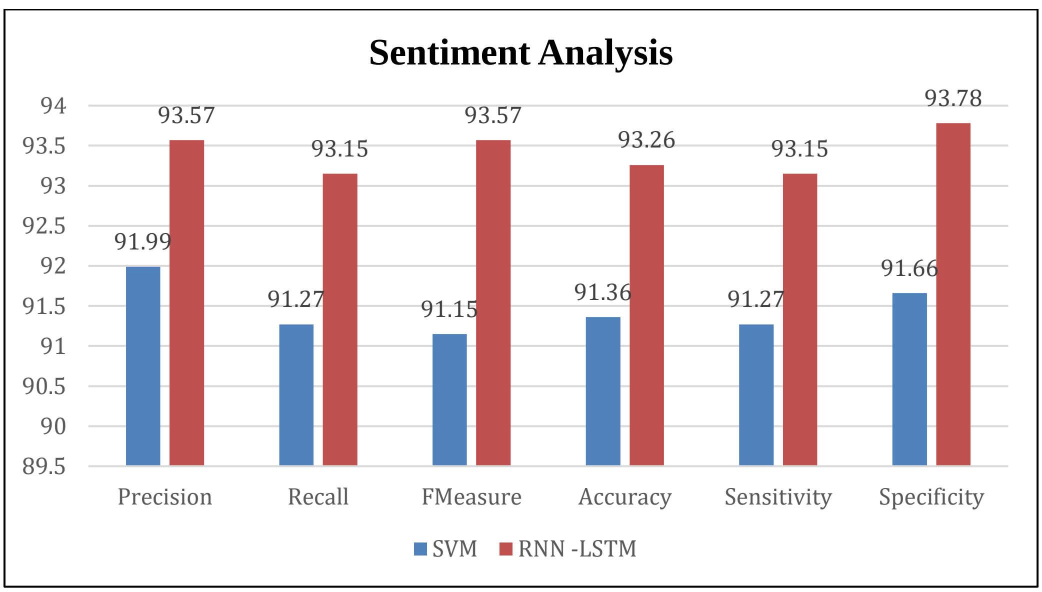

Figure 3 Analysis of Classifiers

Challenges in Sentiment Analysis

In terms of sentiment analysis challenges, there are quite a few factors that companies have trouble with if they want to obtain accurate sentiment analysis results. Natural language processing can make sentiment or emotion analysis more challenging, for the simple reason that machines have to be trained to analyze and understand emotions as human brains do. This is in addition to their ability to interpret the nuances of different languages (Yasumasa et al., 2016). Due to a large number of various websites, finding and monitoring online opinion pages, as well as distilling the data obtained there, remains a challenging task. Each site usually includes a considerable amount of opinionated text that is not always easy to comprehend in extended forum postings and blogs (Duyu et al., 2015).

- The public does not always express their feelings/sentiment in the same way, for example, some express their feelings through ratings and others through comments.
- When a user makes a positive comment about a product, it may be regarded as positive in one context and bad in another.
- People may make false comments about a product, resulting in a negative review of the product.
- Some people don't express opinions as it is.
- Most reviews will include both good and negative feedback, which may be managed by looking at each sentence at the same time.

Conclusion

There is a probability that sentiment analysis may become so advanced and pervasive that it will be difficult to avoid it. This blend of ML and NLP provides insight into the mood and sentiment that drives user interaction with any advertisement, brand, or event. Sentiment analysis was once thought to be unsuccessful since humans can tell whether a response is favourable or negative based on context signals if they try hard enough - a trait known as pragmatic intuition. Advanced AI algorithms and huge data, on the other hand, have aided sentiment analysis techniques in approaching human-level performance. Sentiment analysis will soon be required for comprehending online human interactions and turning them into something that can assist employers or companies in decision-making processes. More and more of our web data will be used to develop emotional intelligence-powered human touch point strategies.

In this proposed work, we tested a model by using RNN-LSTM and support vector machine (SVM) on datasets of customer reviews to find the polarity of sentiments and texts whether positive or negative. In this report, the performance resulting from the Support Vector

Machine (SVM) and the RNN-LSTM was examined to determine accuracy, recall, precision, and f-measure. It has been verified that the RNN-LSTM algorithm achieves a 93.26% accuracy, and it is found to be a robust and better algorithm. Some of the suggestions for future work in this field are that efficient modification can be done in the sentiment analysis of the proposed RNN-LSTM.

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