IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 7, April 2024

Consumer Sentiment is Extracted from the e-Commerce Website Evaluates Dataset using an Assembly Model

Shiva Singh Bhadoria[1], Deepak Gupta[2], Pradeep Yadav[3]

Research Scholar, Department of Computer Science and Engineering[1]

Associate Professor, Department of Computer Science and Engineering[2,3]

Institute of Technology & Management, Gwalior, India

shivasingh46@gmail.com, deepak.gupta@itmgoi.in, pradeep.yadav@itmgoi.in

Abstract*:* *Globe is getting more digitalized in the modern-day. E-commerce is gaining traction in today's digitalized world since it enables customers to purchase products without leaving their homes. As more customers rely on online purchases, the value of a review grows. For a product to be selected, a consumer has to examine thousands to grasp the product. However, in this age of burgeoning machine learning (ML), sorting by hundreds of assessments will be much easier if the model were employed to polarize and learn from those evaluations. In this study, the Python language is used to apply the classification algorithm for the obtained data. The accomplishment of a voting classifier consisting of other three classifiers which are SVC, XGB, and XtraTree demonstrates greater precision than other previous research done. The dataset used here is Amazon product Review and work is implemented on Python 3.1.*

Keywords: E-commerce, Product Review, Machine Learning, Supervised learning, Amazon Dataset

I. INTRODUCTION

The sentiment is defined as an emotion-driven attitude, opinion, or judgment. Sentiment analysis (SA) [1], sometimes called opinion mining, is the study of people's attitudes about certain entities. The internet offers a great deal of information in terms of sentiment. From a user viewpoint, individuals may publish their content on a variety of social media (SM) platforms, including microblogs, forums, & online SNSs (Social Networking Sites). From the researcher's viewpoint, several social media sites publish their application programming interfaces (APIs), allowing researchers & developers to gather and analyze data. E.g., At the moment, Twitter provides three different API versions [2]: The REST API, Search API, and Streaming API all comprise the REST API. The REST API is used to collect user information and status data; the Search API is used to query particular Twitter material, and the Streaming API is used to collect Twitter content in real-time. Additionally, developers may mix these APIs to build unique applications. As a result, SA seems to have a robust foundation, backed up by enormous amounts of online data [3].

However, these kinds of online data include several faults that may obstruct the SAmethod. 1st issue is that, since anyone may publish their material without restriction, the quality of their views cannot be verified. For instance, rather than exchanging viewpoints on a particular subject, internet spammers publish spam on forums. Some spam is completely useless, while others include irrelevant views, often referred to as false opinions [4]. Second, such online data is not necessarily reliable. Ground truth is more akin to a label attached to an opinion indicating its goodness, badness, or neutrality. Stanford Sentiment 140 Tweet Corpus [5] is a publicly available ground truth dataset. Corpus includes 1.6 million Twitter messages that have been machine-tagged. Each message is labeled according to the emoticons (positive and negative) found inside.

In today's world, any company must take customer feedback into account. Customers' feelings are taken into account when designing goods & services. Before using a program or buying a product, potential consumers consider the thoughts and feelings of current users. Furthermore, researcher [6] uses this data to do an in-depth study of industry dynamics and customer preferences. These types of opinions could lead to good forecasting in the stock market.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 7, April 2024

Nevertheless, it remains a huge challenge to discover and monitor the websites and to disclose the information that is found in them, given their abundance. Each site typically has a huge number of opinions, not always simple to decrypt on long forum postings and blogs.

II. LITERATURE SURVEY

Some of the research work which guides in the way of completing this research paper is discussed below:
Hu and Liu [7] The list of positive and negative terms based on customer feedback was summarized accordingly. The positive list includes 2006 words with 4783 words for the negative list. In both lists, there are also some misspelled words, often seen in SM content. Sentiments classification is a classification problem where characteristics comprising information about views or feelings should be discovered before classification.
Pang & Lee [8] presentedthe removal of objective phrases by removing subjective ones for feature selection. They suggestedthe technique of text categorization, which may identify subjective content with minimal cuts.
Gann et al. [9] 6,799 Tokens chosen dependsupon Twitter data, where sentiment score is provided to each token, specifically Total Sentiment Index (TSI), with a positive or negative token.
Callen Rain [10] The present work on Natural Language Processing (NLP) has been suggested to be extended. To categorize a review as positive or negative, naive Bayesian and decision list classifiers were employed.
Maria Soledad Elli and Yi-Fan [11]The sentiments were extracted from the review and the outcome was analyzed to create a business model. They stated that this tool provided them with a fair amount of accuracy. They utilized Multinomial Naive Bayesian (MNB) and supported the major classifiers with a support vector machine (SVM).
In this article [12], the 'Apache Spark' fast and memory-based calculation framework extracts live tweets & analyses sentiment. The main objective is to offer techniques in noisy Twitter streams to analyze sentiments. This article reports on the development of SA, which extracts many tweets. Results categorize user perceptions into good and negative perceptions through tweets.
Usually, classification task includes training & testing data comprising of certain data instances. There are a single goal value or class labelalso many attributes/features in each instance in the training set. The objective of SVM is to develop a model that predicts in test set the target value of data instances, which have just characteristics. In conventional text classification and usually superior to Naive Bayes, SVM is extremely efficient. In contrast to Naive Bayes they are not probabilistic, but huge margins. They consider internet hotel reviews in this case. They offer a supervised machine learning method based on the unigram feature and the TF-IDF to accomplish document polarity classification [13].
According to recent research, the best-known vendor has a growing number of sales. The promotion of trustworthy involvement, however, also incites bad actors to unjustly push their reputation for more. In practice, dishonest evaluations or ratings have already become a serious issue. Their main objective is thus to recognize unfair evaluations of Amazon reviews via sentiment analysis utilizing supervised learning methods in an e-commerce context. [14].
This research examines and categorizes the kinds of comments on prominent Hollywood Movie Trailers produced by YouTube users to determine how these users' sentiments may influence the first day's revenues. Show also the trend in box office income depending on the sentiments after the movie has been released. This will assist distributors and moviemakers in determining the response rate for the movie in advance by analyzing the comments on the trailers, and then, after the film is out, the next day's profits may be anticipated by examining current sentiments. [15].
The article is structured in form of section Ias an introduction, section IIas literature review, section III as proposed methodology, and Section IV results, & snapshots, also lastly section V conclusion & future work.

III. PROPOSED METHODOLOGY

Problem statement

A product may have thousands of reviews on an online buying platform and it is difficult for one individual to evaluate all these reviews. The goal of this work is to build a supervised learning model to separatea huge number of unlabeled product review datathat can give a statistical report on the number of reviews where the customer is not satisfied with a specific feature of Amazon product. To evaluate several classification methods on Amazon data sets in emotional analysis to determine whether it performs well in certain specific areas, by utilizing sentimental analysis on different algorithms for machine learning.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 7, April 2024

Preprocessing:

Preprocessing data is a technique in data mining that allows raw data to be converted into an understandable format. Real-world statistics are often incomplete, unreliable, ordeficient in any action or patterns, and include several mistakes. We removed unique characters and numeric values for our study and translated all letters into smaller instances. Snowball stemmer: a little string processing language for the development of stemming algorithm for knowledge retrieval. Snowball: Snowball Stemming effectively eliminates a term suffix or returns it to its source term. For eg, if we take "ing" from "flying" we get a term or a root term from "flying." "flying" is a verb, and the suffix is an "ing" "ing." This suffix is used to build a separate term from the initial. The word matrix of a concept is then defined as the term frequency for each word is recorded in each case by concept term. We begin with the Words Sack, which displays the documents, and then count the number of occasions a word appears within each text. The next step is to split data between preparation & assessments by splitting the data collection between 90% or 10%.

The evaluation of data collection would be evaluated. The next step is to submit the classification algorithm and get the results by splitting the dataset into training and testing in a 9:1 ratio. A vote is one of the easiest ways to merge several learning algorithms with predictions. Voting classification is not a classifier in and of itself, but a wrapper for many others that have been fitted and graded simultaneously to make use of each algorithm's unique features.

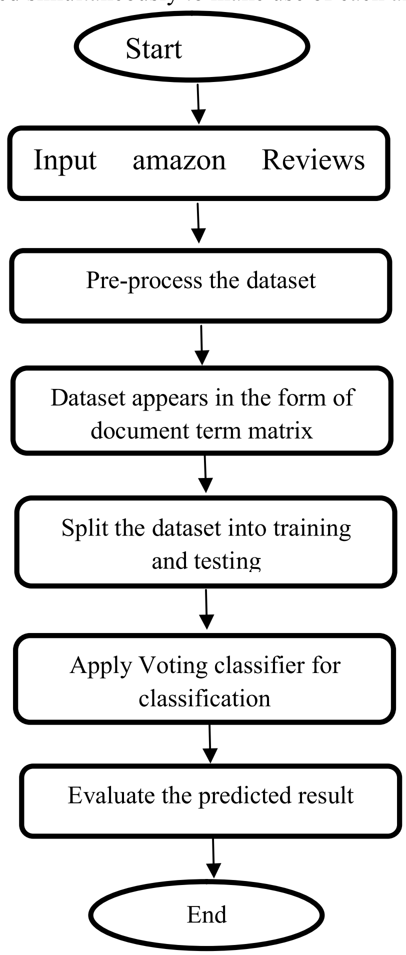

Fig. 1: Data flow diagram of the proposed technique

A VC (Voting Classifier) is a kind of ML model, which trains on an ensemble of many models & predicts output (class) depending upon the class with the greatest chance of being selected as output. It just aggregates results of every classifier that is given into VC and forecasts output class depends upon the class with the greatest voting majority. Rather than building specialized models for each output class and determining their accuracy, we generatea single

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 7, April 2024

model that trains on these models and forecasts output depending upon their aggregate majority of voting for every output class.

SVC: Linear Support Vector Classifier (SVC) objective is to match data you give, generating a "best fit" hyperplane that divides or categorizes your data. Once you've obtained the hyperplane, you may feed several characteristics into your classifier to get a "predicted" class. It makes this particular method more suited for our purposes, but it may be used in a variety of scenarios.

XGB: XGBoost stands for the eXtreme gradient boosting. XGBoost is an ensemble technique of learning. The trees are constructed progressively to boost such that the mistakes of the previous tree may be reduced by each succeeding tree. Each tree gains knowledge from its predecessors & corrects any lingering errors. Thus, the tree that grows next in sequence would learn from an updated version of the residual tree.

Underlying learners in boosting are poor learners with strong bias and prediction power is only a little better than random speculation. Each of these weak learners provides some important prediction information which allows the boosting method to create a strong learner by combining these weak learners efficiently. The last strong learner shows both the partiality and the variance.

ExtraTree: ExtraTrees Classifier is a decision tree-based ensemble learning technique. As with the Random Forest, the Extra Trees Classifier randomizes certain decisions & subsets of data to reduce excess learning and overfitting from data.

IV. RESULTS AND ANALYSIS

Precision or recall for existing work is calculated as 85.41% and 93.18% as shown in the figure. The average accuracy is 90%.

```
Test Confusion Matrix
[[49  7]
 [ 3 41]]
Voting AUC: 0.9034
Accuracy  : 90.0000%
Precision : 85.4167%
Recall    : 93.1818%
F1-measure: 89.1304%
```

Fig. 2: Shows the confusion matrix, AUC score, Accuracy, Precision, Recall, & F1 score for LinSVC

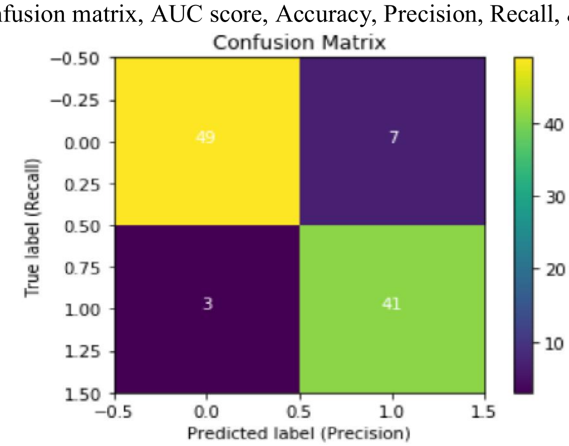

Fig. 3: Confusion Matrix for predicted and true labels

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 7, April 2024

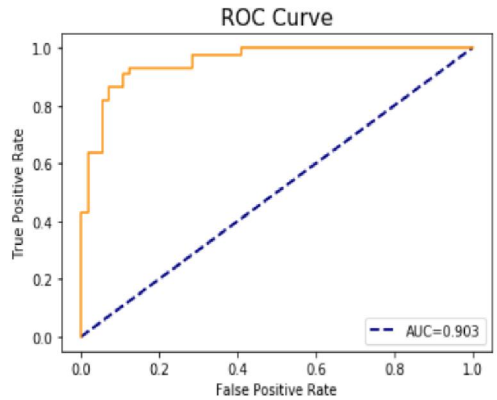

Fig. 4: ROC Curve

AUC — ROC is a method for calculating the output of a classification issue at different levels. The ROC curve is a probability curve, whereas the AUC metric is a measure of the degree of separability. This asks how many models will discriminate between groups. As AUC is larger, the stronger the pattern is 0s as zero and 1s as 1s. The LinSVVC model has obtained a 0.903 value of AUC which is comparatively less than the proposed classifier as shown in figure 6.

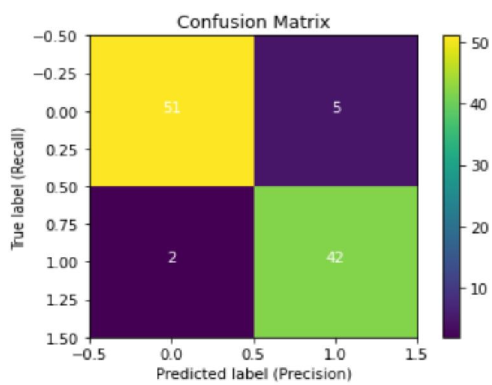

Fig 5: Confusion Matrix Plot

Figures 3 and 5 are the confusion matrix of the base and proposed methodology respectively showing the absolute values of predicted and actual class.

```
Voting AUC: 0.9326
Accuracy  : 93.0000%
Precision : 89.3617%
Recall    : 95.4545%
F1-measure: 92.3077%
```

Fig. 6: Shows the AUC score, Accuracy, Precision, Recall, and F1-measure for Voting classifier

Precision or recall for current research is obtained as 89.361% and 95.45% as shown in the above figure. The average accuracy is 93.00%. Also, the AUC value of the ROC curve is 0.9333

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 7, April 2024

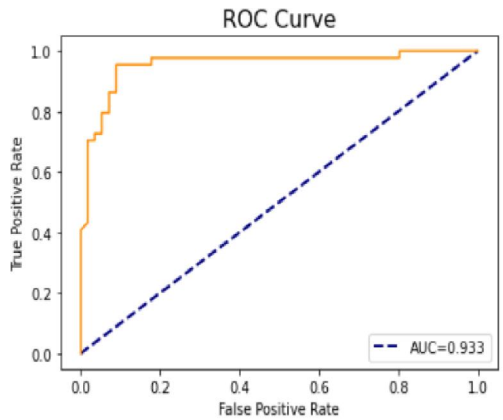

Fig 6: Shows the ROC Curve of the proposed methodology

Table 1: Comparing various parameters of base proposed methodology

Parameters/Algorithms	**LinSVC**	**Voting**
Precision	85.41%	89.36%
Recall	93.18%	93%
Accuracy	90%	95.45%
F1 measure	98.1%	92.3%

V. CONCLUSION

The method is sufficiently accurate for the test case of all Amazon product reviews. We developed a methodology that incorporates established sentiment analysis techniques. Classification of reviews combined with sentiment analysis improved the system's accuracy, resulting in more accurate reviews for the user. Amazon star ratings alone are insufficient for consumers to make purchasing decisions. One should read text reviews to determine which features of the product are unsatisfactory to customers. Thus, this method enables the consumer to purchase the product and also enables the seller or manufacturer to understand the advantages & disadvantages of their product.

In the future, the system may be applied as a web or mobile application with a graphical user interface that enables users to choose a product and see its feature-based rating. Accompanied by rating for every feature, samples of review text for every critical feature may be shown to help the user in comprehending why customers are unhappy with the feature.

REFERENCES

[1]. R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, and P. Kuksa. Natural language processing (almost) from scratch. Journal of Machine Learning Research, 12(Aug):2493–2537, 2011.

[2]. K. Dave, S. Lawrence, and D. M. Pennock. Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In Proceedings of the 12th international conference on the World Wide Web, pages 519–528. ACM, 2003.

[3]. M. S. Elli and Y.-F. Wang. Amazon reviews, business analytics with sentiment analysis.

[4]. S. Hota and S. Pathak. Knn classifier-based approach for multi-class sentiment analysis of Twitter data. In International Journal of Engineering Technology, pages 1372–1375. SPC, 2018

[5]. B. Liu and L. Zhang. A Survey of Opinion Mining and Sentiment Analysis, pages 415–463. Springer US, Boston, MA, 2012

[6]. C. Rain. Sentiment analysis in amazon reviews using probabilistic machine learning. Swarthmore College, 2013

[7]. Hu M, Liu B (2004) Mining and summarizing customer reviews. In: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, New York, NY, USA. pp 168–177

[8]. Pang B, Lee L (2004) A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In: Proceedings of the 42Nd Annual Meeting on Association for Computational Linguistics, ACL '04. Association for Computational Linguistics, Stroudsburg, PA, USA

[9]. Gann W-JK, Day J, Zhou S (2014) Twitter analytics for insider trading fraud detection system. In: Proceedings of the second ASE international conference on Big Data. ASE

[10]. C. Rain. Sentiment analysis in amazon reviews using probabilistic machine learning. Swarthmore College, 2013.

[11]. M. S. Elli and Y.-F. Wang. Amazon reviews, business analytics with sentiment analysis.

[12]. Amandeep Kaur, Deepesh Khaneja" Sentiment analysis on Twitter using apache spark." International Conference on Computing, Communication, and Automation (ICCCA), 2016., vol. 1, pp. 1–5,2016.

[13]. Han-xiaoshi, Xiao-jun "Sentiment Analysis in Hotel Reviews Based on Supervised Learning." International Conference on Machine Learning and Cybernetics, 2011.

[14]. Samha, Xu,Xia, Wong & Li "Opinion Annotation in Online Chinese Product Reviews." In Proceedings of LREC conference, 2008.

[15]. S. Paknejad, "Sentiment classification on Amazon reviews using machine learning approaches," 2018.