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PRODUCT OVERVIEW SENTIMENT ANALYSIS USING LEXICON HYBRID-BASED APPROACH AND MACHINE LEARNING

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Abstract
Various sentiment analysis methods have been proposed to obtain reviewing opinions from machine learning and vocabulary-based sentiment. In previous research using only machine learning methods, I got an unsatisfactory accuracy score because a lexical / lexicon hybrid method was used in this study. Machine learning is proposed that can improve the performance of existing sentiment analysis. With this proposal the researcher was able to obtain experimental results that showed that the classifiers that produced the best results for the game review were Hybrid Lexicon and Nave Bayes with an accuracy of 70%.
Keywords : Sentiment Analysis, Naïve Bayes, Support Vector Machine, Lexicon Based Sentiment

Abstrak
Berbagai metode analisis sentimen telah diusulkan untuk mendapatkan opini ulasan dari pembelajaran mesin dan sentimen berbasis kosa kata. Pada penelitian sebelumnya yang hanya menggunakan metode machine learning, saya mendapatkan nilai akurasi yang kurang memuaskan karena pada penelitian ini digunakan metode hybrid leksikal/leksikon. Pembelajaran mesin diusulkan yang dapat meningkatkan kinerja analisis sentimen yang ada. Dengan proposal tersebut peneliti dapat memperoleh hasil eksperimen yang menunjukkan bahwa pengklasifikasi yang menghasilkan hasil terbaik untuk game review adalah Hybrid Lexicon dan Nave Bayes dengan akurasi sebesar 70%.
Kata Kunci : Analisis Sentimen, Naïve Bayes, Support Vector Machine, Sentiment Based Lexicon

INTRODUCTION

A review is a rating of a publication, service, or company, such as a movie (movie review), video game (video game review), musical composition (musical review of a composition or recording), books (review of a book), shows and others. In this modern era, reviews are used as a tool to determine a selling point. Reviews are usually done by a user, but there are several websites that provide reviews, such as Rotten Tomatoes (Movie Reviews), IMDB (Internet Movie Database), Metacritics (Game Reviews), IGN (Game Reviews). of games) and others. The purpose of a review is to criticize something that will be useful and beneficial to the community and users in general. The ratings or reviews that can be made are not arbitrary, because in the future they will have a significant impact on the audience's response to a product or article under study. The text of the review plays a very important role or has a big impact on the reader's knowledge. With the growing amount of information available on the internet and the substantial increase in the number of internet users, it has become important for ecommerce sites to use a referral system to keep their customers informed about the products they are most likely to purchase. In the context of information filtering, the Recommendation System must be able to provide accurate recommendations to users by extracting valuable facts from the vast amount of information created on the Internet every day.[1] Nonetheless, it is difficult to analyze because each review consists of unstructured text of low descriptive quality and only a third of it is truly informative.[2,3] And popular applications can receive up to thousands of reviews per day.[4] With this paper, we hope to be able to help and analyze a product/service based on written reviews. This article aims to create a system capable of knowing the opinion of reviewers (opinion mining) on a product or service, in which we will use a hybrid method combining based learning and vocabulary. After conducting the experiment, we will find out how effective the method is. To create a good system, we need to make sure the system can work and function correctly for all datasets on which we will be using a product revision dataset. Today, reviews consist of not only plain text, but too much modern content, including emoticons, acronyms ("LOL", "OMG", etc.) and slang ("Nah", "meh", "giggle", etc.). This practice of using modern content elements makes the analysis of sentiment problematic.[5] In previous research conducted using only the machine learning method, we got an unsatisfactory accuracy score, so the researcher wanted to create a hybrid method between vocabulary and machine learning that was shown to improve sentiment analysis performance. The hybrid runs in stages for better accuracy results. This hybrid model is a combination of two methods which are believed to have a high level of accuracy. And many studies conclude that the hybrid model can increase the value of predictive accuracy. Therefore, we will try to hybridize between Naïve Bayes, SVM and the feeling of the lexicon method. After performing a literature review, the researchers found that SVM and Bayes Craft have a higher level of utilization than other

[1] Li Chen, Guanliang Chen, and Feng Wang, "Recommender Systems Based On User Reviews: The State of The Art," *User Modeling and User-Adapted Interaction* 25, no. 2 (2015), https://doi.org/10.1007/s11257-015-9155-5.

[2] Ning Chen et al., "AR-Miner : Mining Informative Reviews for Developers from Mobile App Marketplace," in *Proceedings of the 36th International Conference on Software Engineering*, ICSE 2014 (New York, NY, USA: Association for Computing Machinery, 2014), https://doi.org/10.1145/2568225.2568263.

[3] William Martin et al., "A Survey of App Store Analysis for Software Engineering," *IEEE Transactions on Software Engineering* 43, no. 9 (2017), https://doi.org/10.1109/TSE.2016.2630689.

[4] Dennis Pagano and Walid Maalej, "User Feedback In the Appstore: An Empirical Study," in *2013 21st IEEE International Requirements Engineering Conference (RE)*, 2013, https://doi.org/10.1109/RE.2013.6636712.

[5] A. Mahadevan and M. Arock, "Integrated Topic Modeling and Sentiment Analysis: A Review Rating Prediction Approach For Recommender Systems," *Turkish Journal of Electrical Engineering and Computer Sciences* 28, no. 1 (2020), https://doi.org/10.3906/elk-1905-114.

machine learning. The two-machine learning also get pretty good accuracy results compared to other methods, so researchers will use them. Also, we will merge the two-machine learning together with Lexicon and hopefully get better results than the others.

Related Works

Article by Mudinas et al. discusses the pSenti sentiment analysis method that combines lexicon-based and learning-based methods for generating concepts.[6] The use of two datasets (CNET software reviews and IMDB movie reviews) confirmed the value of the proposed hybrid method for advanced systems such as SentiStrength. In this experiment, they achieved an accuracy of 89.64%. In the article by Malandrakis et al. they achieved 85.80% accuracy using lexicon-based methods and bigram language models with the database being used is Twitter.[7] Article by Sommar and Wielondek article suggests a hybrid approach to improve the efficiency of the impact analysis process.[8] The programming language chosen for the implementation of this algorithm is Python. The proposed algorithm has three steps after the pre-processing, the first part refers to the lexicon model based on finding the best parameters for classification. the second part refers to models based on learning and deals with the analysis of the best models. Finally, the third part refers to the hybrid model that evaluates and determines the optimal MID ratio. They achieved an accuracy of 79.67%. The hybrid method proposed by Heikal et al. is designed as a sensitivity analysis method for Arabic.[9] Their model achieved an F1 score of 64.46%, which is higher than F1's deep learning score of 53.6%. they use a dataset: the Arabic Sentiment Tweets Dataset (ASTD). Their method combines a Convolutional Neural Network (CNN) model with long-term memory (LSTM). In an paper, they propose to improve Twitter influence analysis by using a mixed subject-based model and semi-supervised training.[10] The purpose of this study is to present different methods for high impact analysis on Twitter. Tests show weight adds a 2% improvement and the global effect mode achieves an average F-score of 69.7 with all features combined. In an article by tang et al. we present TS-Lex, which is a unique

[6] Andrius Mudinas, Dell Zhang, and Mark Levene, "Combining Lexicon and Learning Based Approaches for Concept-Level Sentiment Analysis," in *Proceedings of the First International Workshop on Issues of Sentiment Discovery and Opinion Mining*, WISDOM '12 (New York, NY, USA: Association for Computing Machinery, 2012), https://doi.org/10.1145/2346676.2346681.

[7] Nikolaos Malandrakis et al., "SAIL: A Hybrid Approach to Sentiment Analysis," in *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013)* (SemEval 2013, Atlanta, Georgia, USA: Association for Computational Linguistics, 2013).

[8] Fredrik Sommar and Milosz Wielondek, *Combining Lexicon- and Learning-Based Approaches for Improved Performance and Convenience in Sentiment Classification*, 2015.

[9] Maha Heikal, Marwan Torki, and Nagwa El-Makky, "Sentiment Analysis of Arabic Tweets Using Deep Learning," *Procedia Computer Science*, Arabic Computational Linguistics, 142 (2018), https://doi.org/10.1016/j.procs.2018.10.466.

[10] Bing Xiang and Liang Zhou, "Improving Twitter Sentiment Analysis with Topic-Based Mixture Modeling and Semi-Supervised Training," vol. 2, 2014, https://doi.org/10.3115/v1/P14-2071.

large-scale Twitter dictionary based on representational learning techniques.[11] Erşahin et al. presents a proposed hybrid approach that aims to improve the accuracy of machine learning algorithms for impact analysis by providing them with new lexicon-based features.[12] In the article by Janjua et al., they use multiple classification methods between Random Forest (RF), Support Vector Classifier (SVC) and 7 others to compare classification methods.[13] The application of the proposed hybrid method showed a better performance and efficiency of the proposed method, validated on several Twitter datasets to obtain different models. They achieved better results for all Twitter datasets used for the validation purpose of the proposed method with an accuracy of 78.99%, 84.09%, 80.38%, 82.37%, and 84.72%, respectively, compared to the baseline approaches. In the article by Pasupa and Ayutthaya, they offer steps using an examination of the Thai-SenticNet 5 corpus.[14] The framework works different types of features such as word placement, part of speech, emotional recognition and all combinations of these plans. In addition, we combined deep learning algorithms with convolutional neural networks (CNN) and Bidirectional Long Short-Term Memory (BLSTM) - in different ways and compared to many others mixed mix. In the article by Appel et al., they are state that these types of organizational issues are common in the form of the format Finding automatic learning, system as an outfit like the pool, or vector of support (SVM) or a non-interested. Learning through Modeling (UML).[15]

In this paper we are going to discuss sentiment analysis using a hybrid method between lexicon and machine learning. In this section the researcher will explain what method the researcher will use and some of the methods that have been used by several previous researchers.

Sentiment Analysis

Sentiment analysis or opinion mining is the computational study of people's opinions, attitudes, and emotions towards an entity. Entities can represent individuals, events, or topics.

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[11] Duyu Tang et al., “Building Large-Scale Twitter-Specific Sentiment Lexicon : A Representation Learning Approach,” in *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers* (COLING 2014, Dublin, Ireland: Dublin City University and Association for Computational Linguistics, 2014).

[12] B. Erşahin et al., “A Hybrid Sentiment Analysis Method for Turkish,” *Turkish Journal of Electrical Engineering and Computer Sciences* 27, no. 3 (2019), https://doi.org/10.3906/elk-1808-189.

[13] Sadaf Hussain Janjua et al., “Multi-Level Aspect Based Sentiment Classification of Twitter Data: Using Hybrid Approach In Deep Learning,” *PeerJ Computer Science* 7 (2021), https://doi.org/10.7717/peerj-cs.433.

[14] Kitsuchart Pasupa and Thititorn Seneewong Na Ayutthaya, “Hybrid Deep Learning Models for Thai Sentiment Analysis,” *Cognitive Computation* 14, no. 1 (2022), https://doi.org/10.1007/s12559-020-09770-0.

[15] Orestes Appel et al., “A Hybrid Approach to the Sentiment Analysis Problem at the Sentence Level,” *Knowledge-Based Systems*, New Avenues in Knowledge Bases for Natural Language Processing, 108 (2016), https://doi.org/10.1016/j.knosys.2016.05.040.

This topic will most likely be covered by the review.[16] The beginning and growth of this field coincided with social networks on the web, for example reviews, discussion forums, blogs, micro-blogs, Twitter, and social networks, so for the first time in the history of mankind, researchers they have large volumes of opinion. data recorded digitally.

Sentiment analysis itself has several approaches, namely, rule-based approaches that use a set of already available rules commonly created by humans to help identify the subjectivity of a feeling. Automated approaches, unlike rule-based approaches, are not based on a man-made rule, but rather on machine learning techniques in which classifiers typically process text and return it in the form of categories (positive, negative, and neutral). Then there are also hybrid approaches that generally combine rule-based and automated approaches. The advantage of this approach is that generally more accurate results are obtained.

Machine Learning

The supervised machine learning component is not only responsible for small tasks like adjusting sentiment values or finding more sentiment words but is responsible for evaluating all penny-time materials including semantic rules to get the final output.[17] Machine learning describes the systems capacity to learn from problem-specific training data to automate the process of creating analytical models and completing related tasks.[18] Machine learning can be defined as a combination of methods to automatically detect the available patterns in each data set it uses undiscovered patterns to forecast future data or to implement decision making under uncertainty.[19] SVM are a supervised machine learning method it is related to the learning algorithms that analyze the data in the dataset used for classification the svm model separates and constructs hyperfields this hyperfield can be used for classification.[20] Just like SVM, naive bayes also includes supervised machine learning where nb is a machine learning algorithm for classification with computational efficiency and good accuracy bayesian naive in machine learning is a popular classification algorithm based on the application of bayes theorem it is

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[16] Walaa Medhat, Ahmed Hassan, and Hoda Korashy, "Sentiment Analysis Algorithms and Applications: A Survey," *Ain Shams Engineering Journal* 5, no. 4 (2014), https://doi.org/10.1016/j.asej.2014.04.011.

[17] Mudinas, Zhang, and Levene, "Combining Lexicon and Learning Based Approaches for Concept-Level Sentiment Analysis."

[18] Ayushi Chahal, Preeti Gulia, and Department of Computer Science and Applications, Maharishi Dayanand University, Rohtak, India., "Machine Learning and Deep Learning," *International Journal of Innovative Technology and Exploring Engineering* 8, no. 12 (2019), https://doi.org/10.35940/ijitee.L3550.1081219.

[19] Nitin Pise and Saurabh Dorle, "Sentiment Analysis Methods and Approach: Survey," *International Journal of Innovative Computer Science & Engineering* 4, no. 6 (2017).

[20] Lakshmana Kumar Ramasamy et al., "Performance Analysis of Sentiments in Twitter Dataset Using SVM Models," *International Journal of Electrical and Computer Engineering (IJECE)* 11, no. 3 (2021), https://doi.org/10.11591/ijece.v11i3.pp2275-2284.

often used for document categorization ie the classification of documents into one or more categories or classes such as spam or not spam.[21] Random forests have gained popularity in recent years because the performance of various algorithms is exceptional for classification tasks in some areas such as bioinformatics and computational biology.[22] Logistic regression predicates the probability of an outcome that can only have two values (that is adichotomy). The predition based on the use of one or more predictors (numerical and categorial).[23]

Lexicon Based Sentiment

To determine impact analysis and text processing, there are two main methods. The first is a classifier-based method where machine learning is used and the second is a lexicon-based method where sentiment words - dictionaries contain many symbols that define the concepts or values they use to determine the effect of a given text.[24] Impact assessment itself has a variety of methods, namely a rule-based approach that uses existing rules that are often shared by humans to help identify the subject of impact. Automatic methods, unlike rule-based methods, do not rely on human-made rules, but on machine learning methods that process the text and return it as a script (good, bad and neutral). There are also hybrid methods that often combine rule-based and automated methods. The advantage of this method is that accurate results are obtained in general.

RESEARCH METHOD

In this paper, we will discuss sentiment analysis using a hybrid method between lexicon and machine learning. In this modern era writing a review is very important apart from being a provider of information, they contain many things that can help people in choosing the goods or services they will use.

A. Problem identification

The purpose of this study is to find a method that can search and find sentiment analysis from the reviews they wrote using a hybrid method. We will compare several hybrid methods

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[21] Sanjana Agarwal, Nirav Jain, and Surekha Dholay, "Adaptive Testing and Performance Analysis Using Naive Bayes Classifier," *Procedia Computer Science*, International Conference on Advanced Computing Technologies and Applications (ICACTA), 45 (2015), https://doi.org/10.1016/j.procs.2015.03.088.

[22] M. Ali Fauzi, "Random Forest Approach for Sentiment Analysis in Indonesian Language," *Indonesian Journal of Electrical Engineering and Computer Science* 12, no. 1 (2018), https://doi.org/10.11591/ijeecs.v12.i1.pp46-50.

[23] Harshal Pandharinath Patil et al., "Sentiment Analysis of Text Feedback," *IJIRSET* 11, no. 4 (2022).

[24] Rajkumar S. Jagdale, Vishal S. Shirsat, and Sachin N. Deshmukh, "Review on Sentiment Lexicons," 2018, https://doi.org/10.1109/CESYS.2018.8723913.

created previously and find out which method is the best or has the highest effectiveness.

B. Study Literature

In this literature study, various methods used in sentiment analysis will be compared. This is an important thing that we need to do because we need to look for research that has been done before, from this literature study we will get a lot of knowledge about sentiment analysis, Lexicon based sentiment and, machine learning.

C. Data collection

The data is obtained from a BoardGameGeek review posted on the Kaggle website which contains 15 million data from various boardgame reviews. The data obtained is 15 million, but we do not expect all of them to be used in training and testing because many reviews will be omitted during preprocessing.

D. Pre-Processing

In this preprocessing, the data that we have obtained will be processed because not all the data we have is ideal for use and can cause various errors that we do not want. a user may use excessive capitalization and punctuation (to express his strong dislike, for example) and slang in the display. Also, stop words, such as 'the', 'that', 'is' etc., appear frequently throughout reviews and are not very useful. Therefore, reviews need to be pre-processed to extract meaningful content from each review.[25] In this preprocess we will use Rapidminer studio.

E. Data Spliting

After preprocessing, we need to divide the data to be trained and the data to be tested. Usually, the data is divided into training data and testing data, as the name implies, training data will be used in data training and testing data will be used in evaluation. We will divide the data into 2, namely 80% and 20%. Where 80% we will make training data and 20% into testing data.

F. Lexicon Based Sentiment

At this stage we will score our data with the dictionary that we have, for example wonderful has a good score while ugly/terrible will get a less score. The sentiment lexicon is a list of words and phrases, such as "excellent", "awful", and "not bad", which are assigned a positive or negative score, respectively, reflecting the polarity and strength of the sentiment. The

[25] Nabiha Asghar, “Yelp Dataset Challenge: Review Rating Prediction,” 2016, https://doi.org/10.48550/arXiv.1605.05362.

sentiment lexicon is very important for sentiment analysis (or opinion mining) because it provides sentiment rich information and forms the basis of many sentiment analysis systems.[26] In this stage we will create 2 classes, namely positive and negative. Any review with a rating of <=5 is negative and one with a rating of >5 is positive.

G. Machine learning

At this stage the same as before we will create 2 classes, namely positive and negative. After that we will start training. Training is carried out using 80% of the dataset we have. We will find out which machine learning is the best and compare them. We will use 4 supervised machines learning namely SVM, Naïve Bayes, Logistic Regresion and Random Forest. We get the method after comparing the literature studies that we have done. This method gets the better and best score among other methods.

H. Evaluation

After doing the classification, we test the data that we have separated before. We try machine learning that we have trained with the testing data that we have. After getting the results, we will check whether the results we get are according to our expectations. We will write down the accuracy results that we get in the table. Where we will try accuracy when we only use lexicon, when we use only machine learning, then finally we try when we use the hybrid method. The next stage is to look for precision, recall, and F1 score to evaluate the performance of the sentiment analysis that has been done using the following formula:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

(1) As seen in Equation-1 where TP is True Positive, TN is

True Negative, FP is False Positive, and FN is False Negative. Accuracy is the most used classification evaluation metric. Of all the labels that the model predicted, how many were predicted correctly.

$$precision = \frac{TP}{TP+FP}$$

[26] Tang et al., "Building Large-Scale Twitter-Specific Sentiment Lexicon : A Representation Learning Approach."

(2) The precision in Equation-2 looks for all positively predicted labels and finds out what percentage of them are positive labels.

$$Recall = \frac{TP}{TP+FN}$$

(3) The recall in Equation-3 is also called sensitivity and True Positive Rate (TPR). Of all the positive labels, what percentage are predicted as positive labels.

$$F1\ Score = 2 \times \frac{(Precision*Recall)}{(Precision+Recall)}$$

(4) The F1-Score in Equation-4 is the harmonic average of Precision and Recall. The results range between 0 and 1, with 0 being the worst and 1 being the best. This is a measure of model accuracy.

RESULTS AND DISCUSSION

In this first stage we will score our data with the dictionary we have using the sentiWordNet dictionary. Accuracy, precision, and recall are methods used to evaluate performance in opinion mining. After weget the accuracy we can calculate the precision, recall and F1 Score.At this stage we will hybridize the lexicon scores that we get with naive bayes and SVM. before we do the hybridization, we will try without lexicon which will be a comparison of the results obtained by hybrid We do the hybrid step by adding a variable score sentiment that we get at the lexicon sentiment stage which is then studied by available machine learning. These observations get the results shown in Table 4.5. In the nave Bayes and logistic regresion experiment we get an accuracy of 68% which exceeds SVM with an accuracy of 64% and Random Forest with 63% accuracy. In the hybrid experiment, the hybrid Random Forest results had superior results than the SVM hybrid with 95% and 69%. The accuracy of the four algorithms in will be shown in Table 5.1. From the results above we can enter these numbers into evaluation score. In this study we can conclude that Random Forest does have a better result than other machine learning. In addition, it was also proven in the hybrid lexicon and machine learning experiments got a better result than only using machine learning.

Table 5.1 Evaluation table

	Accuracy	*Precision*	*Recall*	*Score F1*
SVM	0.64	0.73	0.84	0.78
Hybrid SVM	0.69	0.71	0.92	0.80
NB	0.68	0.71	0.93	0.80
Hybrid NB	0.87	1.00	0.88	0.93
LR	0.68	0.73	0.87	0.79
Hybrid LR	0.88	0.95	0.95	0.95
RF	0.63	0.63	1.00	0.78
Hybrid RF	0.95	1.00	1.00	1.00

CONCLUSION

The purpose of this study was to evaluate the performance for sentiment classification in terms of accuracy, precision, recall and f1 score. In this paper, I compare four supervised machine learning algorithms from SVM, Naïve Bayes, Logistic Regresion and Random Forest for sentiment analysis of game reviews. The experimental results show that the classifier that produces better results for game reviews is hybrid lexicon and Random Forest with a 95% accuracy other than that it is proven that a combination of lexicon and machine learning get a better result. For further work we would like to compare more efficient sentiment analyzer.

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