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Battle of Sentiment Lexicons: Wordnet, Sentiwordnet, Textblob and Vader in Web Forum Analysis

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ABSTRACT
Introduction: Sentiment research is essential for evaluating public opinion in a number of industries, including the high-rise real estate sector. Comprehending public opinion offers crucial perspectives for interested parties, facilitating data-driven and knowledgeable decision-making. The usefulness and efficacy of lexicon-based sentiment analysis methods in gauging public opinion against high-rise buildings in Malaysia are investigated in this research.
Objectives:The study's objectives are to examine the efficacy of four lexicon-based sentiment analysis tools: Valence Aware Dictionary and Sentiment Reasoner (VADER), WordNet, TextBlob, and SentiWordNet. In recognizing positive, negative, and neutral attitudes stated in public reviews, it aims to assess their categorization performance and accuracy.
Methods: To examine public opinion on high-rise buildings, the study used a real-world case study. The four lexical dictionaries were used to categorize reviews, and their performance was evaluated by contrasting their capacity to recognize neutral, negative, and positive attitudes.
Findings: The investigation showed that a greater percentage of positive reviews than negative or neutral ones were detected by all four lexicon-based techniques. Positive feelings were most prevalent in WordNet, closely followed by SentiWordNet and VADER. The most successful method for detecting negative attitudes was VADER, which was followed by WordNet and SentiWordNet. VADER found the most evaluations for neutral feelings, but SentiWordNet and WordNet found less. When compared to the other tools, VADER performed better overall. The research did, however, also draw attention to VADER's performance shortcomings, including limited vocabulary, trouble identifying sarcasm, ambiguity, and difficulties with misspelled or short phrases, which sometimes resulted in misclassifications.
Conclusions: For scholars, practitioners, and politicians examining public opinion about high-rise real estate in Malaysia, this study offers insightful information. Through more accurate sentiment categorization, stakeholders may improve their decision-making processes by comprehending the advantages and disadvantages of lexicon-based sentiment analysis technologies.
Keywords: Text Analysis, Sentiment Analysis, Housing, Lexicon, NLP, Decision Making.

INTRODUCTION

The development of information technology (IT) has brought about revolutionary shifts in how people communicate their thoughts and views on a wide range of topics, including services, goods, occasions, businesses, and people [1]–[3]. Microblogging, online forums, blogs, and review websites are examples of Web 2.0 platforms that have become popular avenues for online users to exchange ideas, share information, and share opinions. Unlike marketing-oriented content, the information posted on these networks is regarded as genuine feedback. These platforms' widespread impact has grown dramatically in almost every area of contemporary culture. As a result, the amount of user-generated material has increased dramatically. Online forums, Facebook, Twitter, blogs, YouTube, Flickr, Google reviews, and other social networking sites create millions of entries every day on a variety of subjects, including product reviews. Approximately 28.68 million Malaysians, or 83.1% of the country's total population, utilize social media as of early 2024. With 4.8 million more users between 2023 and 2024—a 20% increase—this indicates a considerable expansion. WhatsApp has 90.7% of users, followed by Facebook (84.9%), Instagram (77%), and TikTok (68.8%). With a 48.6% increase in ad reach over the previous year, TikTok has been growing quickly. Online users as well as businesses, governments, and other interested parties looking to gather and examine public opinion find this information to be a rich and useful resource [4]–[6].

The availability of this data makes it possible to examine how individuals behave and engage with one another on certain subjects. However, the large number of opinionated material present on each site makes it difficult

to separate and analyze this enormous amount of user-generated content. It would be impossible for normal human readers to manually analyze the data. As a result, automated techniques are needed to evaluate and condense this data. The study of people's views, sentiments, assessments, appraisals, attitudes, and emotions on a variety of topics, including goods, services, organizations, people, problems, or events, is known as sentiment analysis, or opinion mining. It is also described as an information extraction and Natural Language Processing (NLP) job that aims to determine if the author's emotion is positive or negative [7]–[9]. Due to its potential usefulness in the decision-making process, sentiment analysis (SA) has garnered a lot of interest from academics and business professionals. SA has been used in many different fields, including as commerce, industry, government, healthcare, real estate, and policy-making, to get insights on public attitudes [10]–[13].

Lexicon-based techniques are among the most often suggested methods for sentiment analysis in previous research. Many lexicon dictionaries have been created and effectively used to address a variety of feelings in different sectors. English-Spanish [18], [19], English-Hindi [20], and Chinese-English [21] are just a few of the multilingual contexts in which SA has been researched. Numerous research have examined how well various lexicons do sentiment analysis on text [14–17]. Nevertheless, the majority of this study is on generic lexicons, which often ignore the extensive usage of internet slang by users of the internet. Additionally, Web 2.0-related sites like microblogs have word limits, which makes using conventional lexicons much more challenging. Furthermore, it might be difficult to decide whether dictionary is better in certain situations or if it can provide the same degree of coverage as specific lexical techniques. Every lexicon has been created using diverse approaches, has special qualities, and yields varied results when used with various kinds of text. In order to perform sentiment analysis on online evaluations of high-rise properties collected from online forums and Google evaluations, this study compares and assesses the performance of WordNet, SentiWordNet (SWN), TextBlob, and the Valence Aware Dictionary and Sentiment Reasoner (VADER). The study's findings are intended to provide a thorough grasp of the vocabulary that is most suited for sentiment analysis, especially when the text uses colloquial language like slang.

SENTIMENT ANALYSIS WITHIN THE HOUSING INDUSTRY CONTEXT.

Due to the growth of Web 2.0 platforms such as review websites, social media, and online forums, sentiment analysis (SA) is increasingly being used in a number of industries, including tourism, politics, and the stock market [22]–[25]. Sentiment analysis has been widely used in many other industries, although it is still relatively new in the property market. Research has shown the importance of emotions and beliefs in influencing house investment and purchase decisions in addition to economic factors [26], [27]. Online platforms and user-generated content provide valuable information on customer sentiment at a lower cost and with more scalability than traditional surveys [16]–[28]. Numerous studies have looked at sentiment analysis in the housing sector utilizing both professional datasets (like newspapers) and user-generated data (like online reviews). Research has shown that

The characteristics of the housing market, including price fluctuations and investment patterns, may be significantly impacted by sentiment obtained from news articles and online assessments [5] [29], [30]. Furthermore, recent studies have examined user perspectives in housing-related decision-making models that include community perceptions, educational environments, and the impact of noise on property prices. These findings demonstrate the growing importance of sentiment analysis in understanding housing market trends and assisting stakeholders in decision-making [7], [21], [22].

LEXICON APPROACHED

The lexicon-based method is built on a dictionary or lexicon that contains opinionated words with specific polarity. A sentiment lexicon is made up of words that are categorized as positive, negative, or neutral based on their polarity. One of two methods—the corpus-based method or the dictionary-based method—is often used to create these lexicons. The dictionary-based approach often uses pre-existing dictionaries, such as VADER, to extract emotion concepts. In contrast, the corpus-based approach searches a big corpus for opinion terms [32]. The development of a new sentiment lexicon and the identification of new sentiment terms from a domain-specific corpus using an existing list of recognized opinion terms are the two major applications of this method [32]. The primary drawback of this method, however, is that it requires a large corpus of all English phrases [33], which diminishes its efficacy in comparison to the dictionary-based method. In contrast, the dictionary-based approach extracts sentiment using a lexical database that contains opinion words. VADER [11],

SentiWordNet [34], and [35] are some of the most popular sentiment lexicons in this field.
WordNet organizes nouns, verbs, adjectives, and adverbs into "synsets," which are collections of cognitive synonyms that each convey a distinct concept. A collection of words that have the same part of speech and may be used interchangeably in certain contexts is called a synset. WordNet 3.0 now has over 117,000 synsets, including around 81,000 noun synsets, 13,600 verb synsets, 19,000 adjective synsets, and 3,600 adverb synsets [36]. Synsets may be connected to one another via semantic links such as hyponymy. SentiWordNet (SWN) is a lexical dictionary built upon the Wordnet lexicon. The SentiWordNet has been widely used due to its extensive coverage of opinion words, which covers almost every emotional phrase in the English language. SentiWordNet has been created in three versions: version 1.0, version 2.0, and the latest version 3.0 [24]. This dictionary uses a WordNet dictionary synset in conjunction with three scores to determine positive, negative, or neutral text polarity. The synsets mentioned in SentiWordNet 3.0 consist of three values: objective (O), negative (N), and positive (P).
The sum of these values is one. For instance, the synset for estimable is P = 0.65, N = 0, and O = 0.35. Text polarity is assessed using PosScore (positive score) and NegScore (negative score). This vocabulary consists of the most popular 147,306 synsets. However, SentiWordNet 3.0 is highly vulnerable to dataset noise in social media datasets. Additionally, it avoids emoticons and internet jargon in favor of established lexicons.
Valance Aware Vocabulary and Sentiment Reasoner (VADER) is a vocabulary and rule-based sentiment dictionary designed specifically for social media sentiment [11]. On social media, slang, emoticons like "smile," and acronyms like "LOL" are often used to express happy feelings. The components of earlier lexicon dictionaries, such as General Inquirer (GI), Affective Norms for English Words (ANEW), and Linguistic Inquiry and Word Count (LIWC), were examined and selected to build this dictionary. VADER has 7500 features as a result. Vader has shown exceptional accuracy in prior study with social media material, movie reviews, and product reviews. Furthermore, VADER has shown many advantages as dictionary-based sentiment: it requires no training data, has outstanding processing speed, allows emoji for sentiment classification, and performs perfectly on social media-type text [15]. Lexicon-based techniques are also very competitive since they demand less effort on the human-labeled text and do not require a training dataset. Table 1 illustrates the lexicon approach's use across several industrial domains.
Table 1: The Application of The Lexicon Approach

Author	Objective	Domain	Data Set	Lexicon Method
Al-Shabi, (2020)	Comparison of Lexicon approach	Financial	Twitter	VADER SentiWordNet, SentiStrength Liu and Hu opinion lexicon AFINN
Medagoda et al., (2015)	Sentiment Lexicon Construction Using SentiWordNet 3.0	General	Online Newspaper	SentiWordNet 3.0
Bonta et al., (2019)	Measure public sentiment on movie review	Entertainment	Review website	NLTK Text blob and VADER
Ikoro et al., (2018)	To improve the accuracy of the Lexicon approach	Energy	Twitter	Sentiment R Hu & Liu opinion lexicon
Vu & Le, (2017)	Proposed a lexicon-based method using sentiment dictionaries with a heuristic method for data pre-processing.	General	Amazon, IMDb, and Yelp	SentiWordNet 3.0 Hu & Liu opinion lexicon
Chalothorn & Ellman, (2013)	Comparison between SentiWordNet and SentiStrength	Terrorist	Online forums	SentiWordNet SentiStrength
Neidhardt et al., (2017)	To assess user engagement and conduct sentiment analysis within an online travel forum.	Tourism	Online forums	SentiWordNet

Park (2020)	Evaluation of customer satisfaction	Cosmetic	Reviews website	SentiWordNet 3.0
Khattak et al. (2020)	To measure customer satisfaction based on novel fuzzy sentiment analysis	Drug, electronic and mobile phone	Twitter and Facebook	Sentiword Net 3.0
Ruscheinsky et al (2018)	Determine the broader relationship between news media sentiment, US with real estate market	Real estate	Online News	Harvard General Inquirer (GI)

METHODS

The dataset was extracted from an online property forum in Malaysia and the Google review site. It comprises textual reviews for a specific housing project, focusing on entries from 2019 to 2022. These reviews pertain to three high-rise residential condominium projects in Malaysia. The polarity of the collected data was analyzed utilizing three distinct lexicon-based sentiment analysis methodologies: WordNet, SentiStrength, TextBlob and VADER. The construction of the sentiment analysis model commenced with tokenizing sentences into individual words and eliminating high-frequency stopwords. Subsequently, the words were represented in a bag-of-words (BOW) format, and part-of-speech (POS) tagging was employed to ascertain the syntactic role of each word within the sentences. The lexicons WordNet, SentiWordNet, TextBlob and VADER were then applied to assign positive and negative sentiment scores to each synset associated with the words.

Data Pre-processing

In sentiment analysis, data cleaning and preprocessing are often critical steps to ensure accuracy, although tools like VADER can sometimes bypass these processes due to their ability to handle factors such as capitalization, punctuation, and colloquial expressions. In contrast, tools such as TextBlob, SentiWordNet, and WordNet necessitate rigorous preprocessing to achieve reliable outcomes. The pre-processing phase is crucial for cleaning the data and eliminating unnecessary symbols to ensure accurate sentiment analysis. Initial pre-processing of raw data is essential to prevent inaccuracies and misleading results. In this study, several pre-processing activities were conducted, including tokenization, conversion to lowercase, spell-checking, stemming, filtering of stopwords, and the removal of symbols and punctuation. Additionally, words were tokenized and tagged. For TextBlob, many preprocessing tasks can be streamlined through the use of the NLTK (Natural Language Toolkit) library. A common initial step involves converting all text to lowercase, thereby maintaining consistency across the dataset. For example, "House" is standardized to "house" to simplify analysis. However, while this step is generally useful, it may not always be appropriate, particularly in cases where proper capitalization is crucial for tasks such as named entity recognition or enhancing translation accuracy. The removal of stop words—common words that carry minimal meaning—is subsequently performed using the nltk.corpus library. This is followed by tokenization, which divides the text into smaller units, or tokens, by excluding punctuation and repetitive words that could distort the analysis. NLTK's pre-trained language algorithms, such as RegexpTokenizer(r'\w+'), are employed to efficiently split sentences into words, excluding punctuation marks. The next step in preprocessing involves Part-of-Speech (POS) tagging and lemmatization. POS tagging identifies the grammatical role of each word (e.g., noun, verb,

adjective) within the text. After this process, lemmatization is performed to convert words to their base or root forms, for example, changing "attempting" to "attempt".
This step ensures that different forms of a word are treated consistently throughout the analysis. Lemmatization, which uses WordNet for mapping, is more precise than simple stemming, as it takes the word's context into account and effectively manages abbreviations and spelling variations. A notable challenge in natural language processing (NLP) is dealing with abbreviations and acronyms, which can complicate analysis and consume considerable resources. Abbreviations increase storage requirements, slow down search processes, and may not always contribute to the analysis. Therefore, normalization becomes crucial to convert abbreviations and clean noisy data, especially when analyzing informal text from platforms like Google review and online forum. Normalization addresses issues of inconsistent vocabulary and abbreviations, thus improving the quality and accuracy of sentiment analysis. The final stage of data preprocessing is noise removal, which involves filtering out extraneous elements such as figures, domain-specific symbols, and code snippets that are irrelevant to the sentiment analysis. This step ensures that the dataset is free from unnecessary information and ready for accurate processing. These comprehensive pre-processing steps were meticulously applied to enhance data quality. Ultimately, a total of 5,340 reviews in the shape of raw data and only a total of 2,631 reviews consisting of sentiment were prepared for subsequent analysis. Figure 1 outlines the stages involved in the data preprocessing workflow.

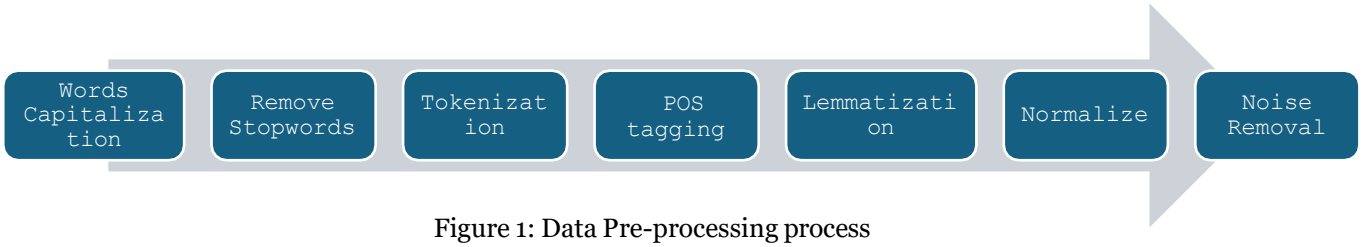
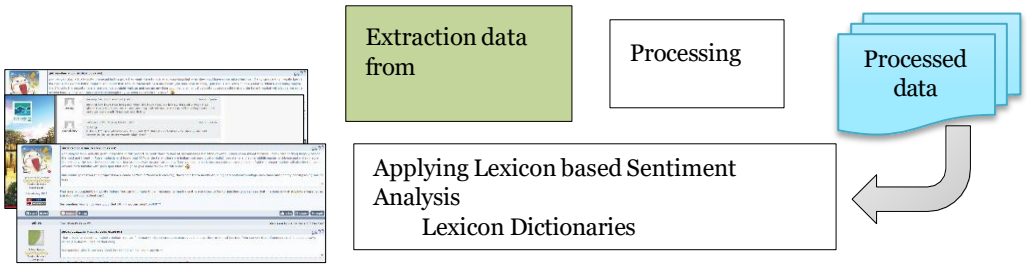


Figure 1: Data Pre-processing process

Sentiment Classification
The next step is to identify the polarity of each review. The lexicon-based model is developed using RapidMiner software, as shown in figure 4.3. The three most used lexicon dictionaries, Wordnet, SentiWordNet, and Valence Aware Dictionary for sentiment Reasoning (VADER), have been conducted. The sentiment score for each review is computed and classified according to specific conditions where;
if(sentiment<0, "Negative",if(sentiment>0 && sentiment !=0, "positive", "Neutral"))
Data Annotation
To ensure the high accuracy of sentiment classification by lexicon dictionary in the previous process, the whole dataset was annotated by humans in this study. Two annotators were proficient in English and well-knowledgeable in the property domain. In this study, proper instruction as a guideline was given to the annotators as in Appendix
A. The annotated dataset was used as a baseline for the validation of each dictionary lexicon classification result. The annotators were tasked with assigning a polarity to each review in the dataset, using two categories: positive and negative. The evaluation of the system's performance in this study was based on four key metrics: precision, recall, F-score, and accuracy. Additionally, the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) values were computed to further assess the system's effectiveness.



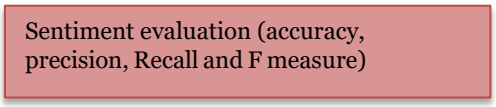


Figure 2: Research framework process

RESULTS

The three most used lexicon dictionaries, Wordnet, SentiWordNet, TextBlob and Valence Aware Dictionary for sentiment Reasoning (VADER). Table 2 presents the distribution of positive, negative, and neutral reviews for the overall projects. It is evident that all three lexicon dictionaries predicted a higher number of positive reviews compared to other polarity sentiments. The sentiment analysis results show that VADER classified 1,528 reviews as positive, 791 as negative, and 312 as neutral. SentiWordNet identified 1,787 reviews as positive, 735 as negative, and 109 as neutral. WordNet classified 1,800 reviews as positive, 759 as negative, and only 72 as neutral. Lastly, TextBlob categorized 1,567 reviews as positive, 710 as negative, and 354 as neutral. These numbers indicate that each dictionary has a different approach to classifying sentiments, with some identifying more positive reviews, while others detect more negative or neutral sentiments. To assess the accuracy of sentiment classification by the lexicon dictionaries, the entire dataset was annotated by human annotators in this study. The annotators were proficient in English and possessed domain knowledge in the property field.

Detailed guidelines and instructions were provided to ensure consistent and accurate annotation. The annotated dataset served as a baseline for validating the classification results of each lexicon dictionary. The annotators assigned each review in the dataset with either positive or negative polarity, as these were the two polarity types considered in this study. The classification results obtained from the lexicon dictionaries were compared with the manually annotated testing data to evaluate their accuracy. Evaluation measures, including accuracy, precision, recall, and F-measure, were calculated and used for comparison. These measures provide a comprehensive assessment of the performance of each lexicon dictionary in sentiment classification. The classification results for each lexicon dictionary are presented in subsequent sections. The utilization of human annotators for manual annotation ensured high accuracy in sentiment classification during the previous process. This approach enhances the reliability of the baseline dataset used for validating the classification results of the lexicon dictionaries. The expertise and proficiency of the annotators, along with the provided guidelines, contributed to the consistency and quality of the annotations. In this study, the focus was on positive and negative polarities, as they are commonly used in sentiment analysis. Future research could explore additional polarity types or more refined sentiment categories to capture a more nuanced understanding of public sentiment towards high-rise properties. Overall, the combination of manual annotation by human experts and the evaluation measures employed in this study ensures a robust assessment of the lexicon dictionaries' sentiment classification accuracy. These findings contribute to the advancement of sentiment analysis methods and their applicability in understanding public sentiment towards high-rise properties in Malaysia.

Table 2: Sentiment polarity classification results for the reviews

Lexicon dictionary	Positive	Negative	Neutral
VADER	1528	791	312
SentiWordNet	1787	735	109
Wordnet	1800	759	72
TextBlob	1567	710	354

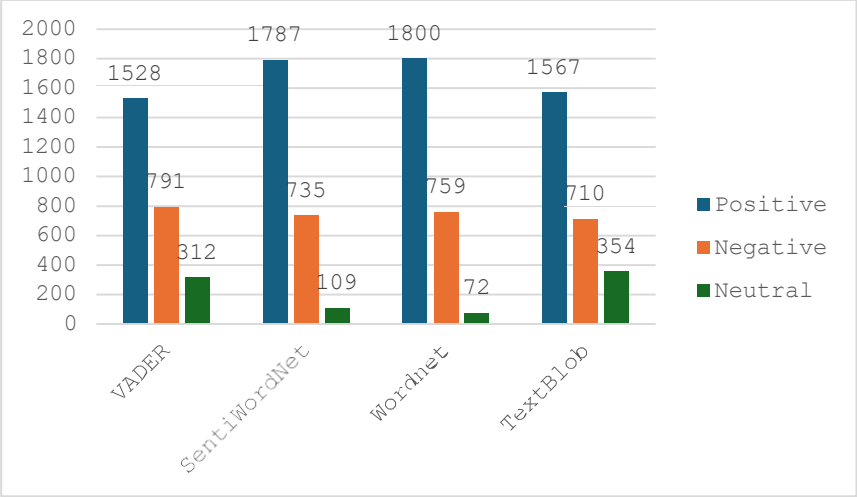


Figure 3: Classification results for the sentiment polarity of the reviews.

Table 3: Annotation's results

Approaches	Positive	Negative
Annotator 1	1362	1269
Annotator 2	1369	1262

This research employs four evaluation metrics: precision, recall, F-score, and accuracy. Additionally, the values for true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) have been computed and utilized to assess the system's. The outcomes from the manual annotation process are displayed in Table 4.
Table 4: The performance measure for each lexicon dictionary

Dictionary	Evaluation matrix	First annotator score	Second annotator score	Average score
VADER	Accuracy	0.778	0.785	0.782
	Precision	0.737	0.749	0.743
	Recall	0.909	0.908	0.909
	F1 score	0.814	0.821	0.817
Wordnet	Accuracy	0.689	0.690	0.690
	Precision	0.648	0.651	0.65
	Recall	0.878	0.877	0.877
	F1 score	0.745	0.747	0.746
SentiWordNet	Accuracy	0.694	0.697	0.695
	Precision	0.653	0.657	0.654
	Recall	0.88	0.886	0.886
	F1 score	0.751	0.754	0.753
TextBlob	Accuracy	0.714	0.734	0.724
	Precision	0.708	0.712	0.71
	Recall	0.890	0.901	0.8955
	F1 score	0.788	0.795	0.7915

As shown in Table 4, the classification results generated by VADER achieved an overall accuracy of 78% for the review sentences, along with a notably high recall rate of 90%. These findings indicate that the VADER lexicon dictionary outperformed the other two dictionaries in terms of sentiment classification. TextBlob as second, SentiWordNet achieved the third-highest accuracy, precision, recall, and F1-score, with only a slight difference in scores with Wordnet. Although the results demonstrate a reasonable level of accuracy for VADER

in this study, it is important to examine the instances where misclassifications occurred. Table 6 provides an overview of the reviews that VADER incorrectly classified, offering insight into the specific cases of misclassification by the VADER lexicon.

Table 5: Example of misclassification by lexicon dictionary

Reviews	Incorrect Polarity	Manually Label Polarity
"good analysis sound pollution factor slowly die because pollution"	Positive	Negative
"developer add sliding sun louvre balcony recent project petalz use project npe highway increase privacy reduce serious sound pollution highway"	Negative	Positive
"Parking lot design kind weird design"	Neutral	Negative

Previous studies have highlighted several factors that contribute to misclassification by lexicon-based sentiment dictionaries. These factors include limitations in the lexicon's vocabulary coverage, the presence of sarcasm in reviews, ambiguity in word meanings, and the use of misspelled or abbreviated terms. Such challenges have been identified as key sources of inaccuracies in sentiment classification using lexicon dictionaries.

DISCUSSION

The purpose of this research was to evaluate the suitability and efficacy of several lexical dictionaries in gauging public opinion on high-rise buildings in Malaysia. Wordnet, SentiWordNet, and the chosen lexicon dictionaries VADER were contrasted according to the accuracy and performance of their categorization. All three lexical dictionaries predicted more favorable evaluations than negative and neutral ones, according to the analysis of all project reviews. The most categorized favorable evaluations were found on Wordnet, closely followed by SentiWordNet and VADER. VADER categorized the most sentences in bad reviews, followed by TextBlob, Wordnet, and SentiWordNet. SentiWordNet and Wordnet received less positive polarity evaluations for neutral ratings than VADER. The outcomes were compared with carefully annotated testing data to assess each lexical dictionary's categorization accuracy. Accuracy, precision, recall, and F-measure were used as assessment metrics. With a significant recall value of 90%, VADER had the maximum accuracy of 78% for all review phrases.

Although SentiWordNet's accuracy, precision, recall, and F1 score were somewhat lower, it still showed good performance. VADER uses two lexicons created especially for social media that take into consideration the subtleties and intensity of online slang and colloquial terms. This explains the reported findings by enabling VADER to interpret text more precisely than others. The instances in which VADER incorrectly categorized evaluations must be taken into account, however. Misclassification was shown to be influenced by vocabulary dictionary restrictions, including word limits, sarcasm, ambiguity, and misspelled or short words. These elements emphasize the need of expanding and improving lexicons in order to improve sentiment categorization accuracy. The study's conclusions advance knowledge of sentiment analysis in relation to Malaysian high-rise buildings. The premise that these assets are often linked to appealing features and facilities is supported by the overwhelming favorable emotion toward them. However, the misclassification situations that VADER found highlight how difficult it is to reliably capture emotion using lexical dictionaries alone. In order to overcome the shortcomings of lexicon dictionaries, future studies should update and extend them to include a greater variety of terms and phrases unique to a certain subject. Furthermore, the efficacy of sentiment analysis models in identifying contextual subtleties and sarcasm may be enhanced by using machine learning and natural language processing methods. This research concludes by highlighting the significance of properly choosing and assessing lexical dictionaries for sentiment analysis in certain areas. In order to make well-informed judgments based on precise sentiment categorization, researchers, practitioners, and policymakers interested in examining public attitude towards high-rise buildings in Malaysia might benefit greatly from the findings.

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