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Myanmar Lexicon Based Sentiment Analysis on Hotel Reviews

Khaing Su Latt[a]*, Myo Khaing[b]

[a,b] *University of Computer Studies, Mandalay, Mandalay-Mogok Road, Patheingyi Township, Mandalay, Myanmar*

[a]*Email: khaingsulatt@ucsm.edu.mm,*[b]*Email: myokhaing@ucsm.edu.mm*

Abstract

As social media and digital communication use increases in Myanmar, sentiment analysis is being used more and more in business, politics, and social trends. Big social data analytics is a valuable tool that can be utilized to uncover significant information from social user data. This methodology integrates diverse statistical techniques, sentiment analysis, multimedia administration, and social media analytics to anticipate and predict individuals and examine patterns. Natural Language Processing (NLP) tools and frameworks are becoming more customizable and easily accessible, which makes the process of creating language models unique to Myanmar easier. The proposed system's lexicon will have six categories of aspects (Room, Staff, Facilities, Location, Value, General), together with their corresponding subcategories and opinion terms. After that, word2vec is used to train the reviews of the annotated corpus and create a word embedding model. Because of the nature of the Myanmar language, it is particularly more difficult to perform aspect-level opinion mining on reviews about Myanmar. As a result, the proposed system's primary goal is to employ syntactic patterns and rules to extract pertinent pairs of attributes and opinion terms from user evaluations. The proposed method could be increase the accuracy of sentiment analysis on social media postings written in Myanmar.

Keywords: Deep Learning; Convolutional Neural Network; Sentiment Analysis; Natural Language Processing; Word2Vector.

1. Introduction

One of the interesting uses of NLP, along with sentiment analysis, machine translation, automated summarization, etc., is text categorization. Overwhelming information is one of the major issues facing individuals today. Individuals squander excessive amounts of time choosing the most interesting information from the multitude of sources available on the internet.

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* Corresponding author.

A strong text classifier can sift through vast volumes of data and extract relevant material. Sentiment analysis is an area of NLP that examines attitudes, beliefs, and feelings that are conveyed in

unstructured data. Polarity classification, which involves categorizing the general sentiment seen in a text or sentence, is a frequently assigned job in this field of study. Classifying a text or statement into three categories—positive, negative, or neutral—usually simplifies this work. Lexiconomy-based techniques and machine learning algorithms are the two primary methodologies that have been researched for creating sentiment classifiers [1].

In the past, a lot of researchers used different machine learning algorithms and their variation models to conduct text categorization. Because deep learning models can now capture semantic word associations, there has been a lot of interest in using them for text categorization in recent years. For any deep learning model to successfully complete a job, a large amount of data is usually needed. The majority of sentiment analysis research has been directed toward several commercial uses, including reviews of movies, products, hotels and other media. An essential part of sentiment analysis systems are sentiment lexicons. There are several emotional lexicons for the English language that were either crowdsourced or painstakingly compiled by specialists [2]. It might be difficult for scholars to create resources like lexicons, dictionaries, and corpus for foreign languages. Due to the lack of corpus resources and tools, including part-of- speech (POS) taggers, lexicons, annotated corpora, and others, sentiment analysis in the Myanmar language is yet unexplored. Formal and casual writing styles usually differ significantly in the Myanmar language.

The structure of this document is as follows. The relevant prior research on sentiment analysis of Myanmar languages is provided in section 2. The nature of the Myanmar Language is discussed in section 3 and then details about sentiment analysis are described in section 4. Section 5 presents the proposed system design and methods. The next section 6 presents the experimental result of the proposed system. Finally, this review concludes the paper in section 7.

2. Related Works

A contemporary area of study in NLP is sentiment analysis, which is concerned with people's perceptions, remarks, sentiments, attitudes, and feelings concerning target items including goods, services, cultures, or even specific persons (politicians). Myanmar is the official language of the country; some Myanmar-related information may be found online. Researchers have been doing sentiment analysis in Myanmar for the past few years. This section describes a few relevant sentiment analysis research projects in the Myanmar language.

In [3], the authors proposed the domain-specific sentiment lexicon for news articles in the Myanmar language. To create the lexicon, they employed chi-square statistics and word correlation. In their work, they used n-gram, word correlation, and chi-square statistic techniques to choose features by constructing a lexicon. The Facebook user comments on news media pages written in Myanmar were subjected to feature selection techniques. Their testing results demonstrated the value of their suggested approach in improving sentiment analysis systems' overall performance across all domains.

In [4], the authors used a bootstrapping method based on syllable n-gram frequencies to develop an opinion lexicon for Myanmar movies. In order to facilitate the automated generation of new opinion terms, a corpus of movie comments, totaling 12,123, was gathered from Facebook Myanmar. In addition, they developed the algorithms for polarity categorization of comments, initial positive seed selection, and first negative seed selection. According to the results of their investigation, syllables bi- and tri-grams were the terms that expressed the most opinions.

In [5], the authors created a senti-lexicon and analysis for Myanmar text restaurant reviews. They gathered 800 reviews—both critical and noncritical—of meals and eateries from Facebook by hand and suggested using them as a resource. The lexicon-based technique was employed to extract opinion words from the reviews. The opinion words related to a restaurant review are included in the senti-lexicon construction of food and restaurants from Myanmar, which they offered. With an overall accuracy of 96%, their algorithm was able to effectively annotate 500 customer evaluations of food and restaurants for the Myanmar Language resource.

In [6], the authors developed the sentiment analysis algorithm as aspect level opinion mining for hotel reviews written in the Myanmar language. Their method examined customer evaluations of hotels that were written in Burmese. The aim was to mechanically extract pertinent subjective data or opinions from a large volume of user evaluations. It classified the characteristics and aspects found in the reviews as negative, positive or neutral after completing the opinion mining assignment at the aspect level. They based their system's implementation on aspect-level opinion mining, which primarily looks for relationships between product attributes and reviewers' opinions.

In [7], using Support Vector Machine, the researchers developed a sentiment analysis method for Myanmar news on Facebook social media. They used the TF-IDF approach for feature extraction and n-gram for feature selection. They produced an annotated corpus in that sense. A 4G crawler was used to gather the data from news websites in Myanmar. They demonstrated that the positive and negative terms from Myanmar's bigrams and unigrams performed better in their experiments.

In [8], the authors expanded the previously established movie domain dataset, extracted Myanmar movie attributes using preprocessing procedures, and used the Naïve Classifier to estimate the polarity of the comments in order to classify them as positive or negative. The primary data sources were user-generated movie comments on Facebook that were posted in the Myanmar language. Using a limited dataset, they provided a detailed explanation of how comments were classified using Naïve Bayes. The difference in the sentiment words was counted to determine the total polarity.

In [13], S.Y. Maw and M.A. Khine presented aspect based Sentiment Analysis for Myanmar Language. In their system, they applied the deep learning approach to better performance. Their approach was implemented on the number of positive words and negative words. Their system was more focused on the classification part. Using the advantages of deep learning, they implemented their system to be the best. The main difference between their system and the proposed system is that they focus on deep learning classification, but this system can create a better Myanmar language lexicon and get a better SA.

These related works can provide valuable insights, methodologies, and approaches for conducting Myanmar lexicon-based sentiment analysis on hotel reviews. Researchers can adapt and extend these methodologies to suit the specific requirements and challenges of sentiment analysis in the Myanmar language and hotel domain. The size of the vocabulary in the Myanmar language is smaller than that of the English language due to the difficulty and magnitude of lexicon formation. The Myanmar language has a very diverse character. As was previously said, there are several methods for sentiment analysis, such as machine learning and lexicon-based methods. Every strategy has advantages and disadvantages. Comparing the two methodologies in the Myanmar language SA is still challenging.

3. Nature of Myanmar Language

The majority of people in Myanmar speak Burmese, also known as Myanmar language, which is the official language of the nation. Burmese script is the script used in Myanmar. It's an abugida, a writing system where vowel sounds are indicated by diacritical marks applied to basic characters that represent consonant-vowel pairs.

There are no gaps between words in the script; everything is written from left to right. Applications of NLP in Myanmar can include entity recognition, topic modeling, and text analytics for sentiment analysis. Because of the peculiarities of the language, these duties might be difficult. A deficiency of complete language resources, such as sentiment lexicons, labeled datasets, and pre-trained language models, impedes NLP for Myanmar. It is difficult to create reliable NLP applications because of this lack of resources.

For the purpose of creating language technologies that can improve communication, meet the needs of the local populace, and offer insightful information for a range of applications, such as business, social media analysis, and information retrieval, it is essential to comprehend the nature of the Myanmar language in NLP. Although there exist obstacles, there is hope for the advancement of NLP resources and applications in Myanmar due to the rising interest and cooperative efforts.

4. Sentiment Analysis

Sentiment analysis falls within the category of NLP, which is the scientific study of human languages from a computational standpoint. NLP is also known as computational linguistics. There are three levels that it may be categorized into: aspect, sentence, and document levels.

At the document level, each sentiment- positive, negative, or neutral-is categorized throughout the whole document. Sentence level: Each sentence in the papers is examined separately and categorized as neutral, positive, or negative. Aspect Level required the user to recognize the elements in a phrase for a particular document, evaluate those elements, and categorize them as neutral, positive, or negative [9].

Sentiment analysis is the process of interpreting words in their context to reveal a brand's social sentiment. It also assists businesses in assessing if the product they are producing will find a market. These days, a lot of information on the Myanmar language was available online. Sentiment analysis (SA) in the Myanmar language is necessary since it is crucial to analyze this massive amount of data in order to extract extremely valuable information. The efforts to develop sentiment analysis systems for Myanmar are reviewed in this study.

4.1. Document Level

Documents are usually categorized into broad sentiment categories, such as mixed, positive, negative, or neutral, using document-level sentiment analysis. More detailed sentiment classifications or emotion labels may be present in some models. At this stage, the overall tone of the entire work is chosen. A variety of methods, such as rule-based systems, machine learning models, and NLP tools, are used in document-level sentiment analysis.

Sentiment analysis at the document level is useful for rapidly determining the general sentiment among massive amounts of textual data. Other types of sentiment analysis, such as fine-grained sentiment analysis or aspect-based sentiment analysis, are better suitable for applications that call for a more in-depth comprehension of sentiment at the sentence or phrase level.

4.2. Sentence Level

Sentence-level sentiment analysis is a subset of sentiment analysis that concentrates on evaluating the sentiment conveyed in single sentences or brief phrases that are part of a longer text, such a social media post, document, or review. This degree of analysis offers a finer-grained comprehension of the text's emotion. Sentence-by- sentence sentiment analysis analyzes the sentiment represented in each sentence by dissecting the text into its constituent parts. For the purpose of classifying sentiment, it treats every sentence as a distinct unit.

Sentences are often categorized as positive, negative, neutral, or mixed sentiments using sentence-level sentiment analysis. More detailed sentiment classifications or emotion labels may be present in some models. Sentence-level sentiment analysis uses a variety of methods, such as NLP tools, rule-based systems, and machine learning models. Sentence-level sentiment analysis comes in handy when you need to identify specific assertions or opinions or when you want to learn more about how sentiment fluctuates within a text. It offers a more in-depth viewpoint on sentiment, which is beneficial for applications that need precise sentiment analysis.

4.3. Aspect Level

A specialized type of sentiment analysis called aspect- level sentiment analysis, often referred to as aspect-based sentiment analysis, focuses on evaluating sentiment in relation to certain characteristics, features, or entities referenced in a text. Aspect-level sentiment analysis looks for the sentiment connected to specific textual elements rather than categorizing the general sentiment of a sentence or document. Textual aspects or entities are identified and extracted as part of aspect-level sentiment analysis. These elements may include characteristics, features, services, or any other elements that are susceptible to sentiment analysis. Every feature has a sentiment score or category (positive, negative, or neutral) connected with it [10].

NLP tools, rule-based systems, and machine learning models are frequently used in aspect-level sentiment analysis. Aspect-level sentiment analysis is critical for applications where users must evaluate how they feel about particular parts of a longer text. Compared to document- or sentence-level analysis, it provides a more thorough and instructive viewpoint on sentiment. A statement that has a target (or subject) and feeling about it is called an opinion. A technique in entity level analysis is this one. This aids in improving comprehension of the sentiment analysis issue.

5. Proposed System

According to the previous work, there are many challenges on their future work such as to reduce their time cost

for training time than other remaining models [11]; to apply other NLP such as semantic web search and spam filtering applications [12] and to solve the complex and huge task: Myanmar Language Lexicons with large amount of corpus. We initiated the process by manually compiling words denoting sentiment from the reviews, which were categorized into six aspects groups: room, staff, facilities, location, value, and general.

Each aspect group includes numerous interconnected aspects and its opinion words. This proposed system collects the emoticons of customers' feeling in reviews. The orientation of the opinion words is assigned positive, negative and neutral. This system converts the orientation of each word into a numeric value to perform further computation i.e. positive is 1, neutral is 0, Negative is -1.

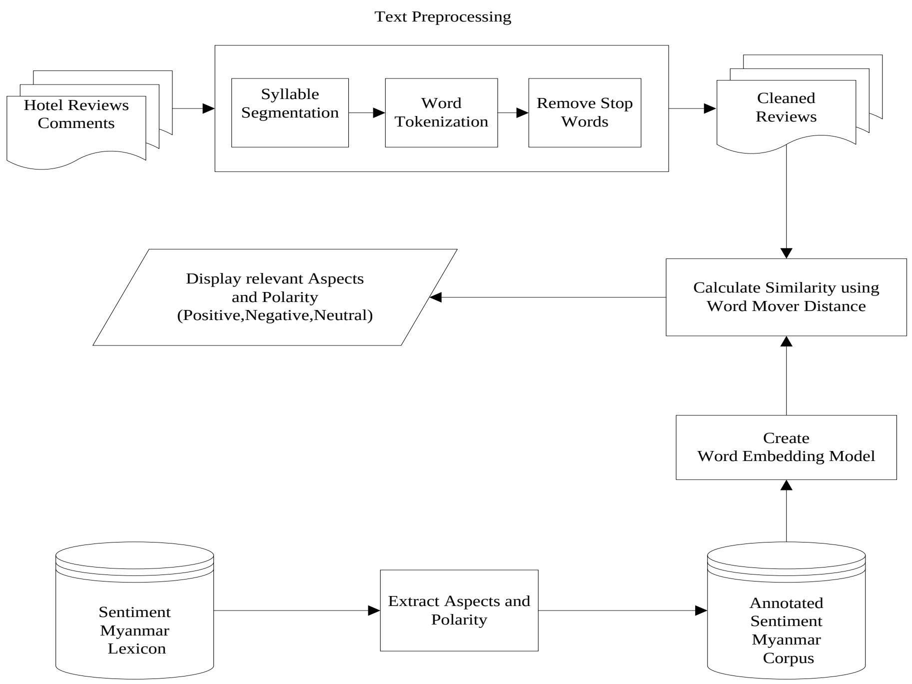

Figure 1: Proposed System

Figure 1 shows the system design of proposed system and then this design represents the flow of the proposed system. This proposed system implements on sentiment analysis of social media posts in Myanmar language, which poses several challenges such as the lack of a comprehensive emotional lexicon and the need for feature

reduction techniques. In this prosed system, new sentiment corpus for Myanmar language are built and trained based on the collected reviews. Myanmar sentiment lexicons for hotel reviews domain are available from Annotated Sentiment Myanmar Lexicon(ASML) and collected reviews. The Web Embedding Model will be created to learn continuous vector representations for words based on their context in a given dataset. And then, the relevant aspect values will be generated by calculating the Word Mover Distance. As the contribution of this proposed system, the new annotated sentiment Myanmar corpus is created for the hotel reviews. And then this proposed system applied the more attractive methods for the better accuracy.

5.1. Data Collection

Reviews and opinions are gathered from hotel booking websites for the proposed method. Only data written in the Myanmar language is gathered in this system; data written in other languages is eliminated. The various ways that opinions, emotions, and feelings are expressed-through terminology, writing context, and the use of slang and abbreviated forms-lead to a large and unorganized amount of data. The text data is written in a combination of formal and informal writing styles, without any segmentation, and includes reviews that are neutral, negative, and positive. Online users can voice reviews that are neutral, good, negative, or occasionally both.

5.2. Data Preprocessing

Preprocessing is the basic step for NLP process and has many steps. Word segmentation, tokenization, and stop words removing processes are used in the proposed system. Myanmar word segmentation is placing spaces into textual data without other replacing or rewriting operations. Myanmar sylbreak3 segmentation is used for syllable segmentation. This segmentation is a useful tool that can make the syllable segmentation, word segmentation, and phrase segmentation for the Myanmar language. Actually, sylbreak tool is working well if the user provided the Myanmar text that typed correct order based on the Unicode standard. Finding the word boundaries in a sentence allows for tokenization, or the separation of words. After segmentation, a step called tokenization divides a segment into tokens so that the longest matching dictionary can find the segment.

The process of dividing a given text into units known as tokens is known as tokenization. Singular words, phrases, or even entire sentences can be used as tokens. Certain characters, such punctuation marks, may be removed during the tokenization process. Typically, tokens are used as input in parsing and text mining procedures. In theory, the texts from Myanmar are divided into morphemes, or as small meaningful units as feasible. In order to increase system performance in classification tasks, stop word removal is a crucial preprocessing approach. The most frequently used words in any natural language that have little to no semantic context in a phrase are known as stop words.

5.3. Creation of Myanmar Sentiment Lexicon

Sentiment Lexicon is a database of lexical elements for a language along with their sentiment orientations, serving as a lexical resource for sentiment categorization. The development of the Myanmar Sentiment Lexicon for the hotel domain is shown in this section. There are no reference materials available in Myanmar language to

categorize sentiment orientation.

By examining the hotel evaluations on social media, this suggested system builds a vocabulary that contains sentiment words related to hotel reviews. Based on system's understanding and continued research, the proposed manually gather sentiment-laden phrases from hotel reviews. System's database of synonyms and antonyms for the Myanmar language is growing. This system assigns the polarity of the sentiment words and emoticons such as positive, negative, and neutral with their target aspects such as room, staff, facilities, location, value, and general. This system collected 2027 reviews which included 1668 positive, 268 negative, 91 neutrals.

5.4. Aspect Specific Sentiment Extraction

The extraction of stated aspect phrases is the main step in our process of extracting aspect-based sentiment analysis. This main phase for aspect-based sentiment analysis is the extraction of the predicted polarity label given a previously identified aspect term. Three labels- positive, negative, and neutral – are used in this step. For

this system, table 1 describes example of aspect in each group for hotel domain.

Table 1: Example Aspect in each Group for Hotel Domain

Room	Staff	Facilities	Location	Value	General
အိပ်ခန်း (Bedroom) အိပ်ယာ (Bed) ခေါင်းအုံး၊ စောင် (Pillow & Blanket) မီး (Light) ရေချိုးခန်း (Bathroom) ရေပူရေအေး (Hot/Cold Water) ဘေစင် (Basin) အိမ်သာ (Toilet) တီဗီ (TV) ရေခဲသေတ္တာ (Refrigerator) လေအေးပေးစက် (Air Conditioner) ပလပ်ပေါက် (Outlet)	ပစ္စည်းသယ်ဝန်ထမ်း (Bell boy) စားပွဲထိုး (Waiter) မန်နေဂျာ (Manager) ပိုင်ရှင် (Owner) ဧည့်ကြို (Front Desk)	အားကစားရုံ (Fintess center) ရေကူးကန် (Swimming Pool) ကျန်းမာရေးနဲ့ အပန်းဖြေ ဝန်ဆောင်မှု (spa) စားသောက်ဆိုင်နဲ့ ဘား (Restaurant and bar) ဝိုင်ဖိုင် (Internet Access) ကားပါကင် (Parking) ဧည့်ခန်း (lobby) လုံခြုံမှု (Security) အဝတ်လျှော် (laundry)	ကားဂိတ် (Bus Station) လေဆိပ် (Airport) မြို့ထဲ (Downtown) မြို့ပြင် (Suburbs)	ဈေးနှုန်း (Price) ဝန်ဆောင်မှုအရည် အသွေး (Quality of Service)	နေထိုင်/ တည်းခို (Living/ Accommodation) အရည်အသွေး (Quality) ဟိုတယ် (Hotel)

5.5. Annotated Sentiment Myanmar Corpus

From that lexicon, a corpus will be built using rules or algorithms. The corpus contains pre-collected reviews, 6 kinds of aspects, and polarity (positive, negative, and neutral). This system aims to identify whether the reviews

evoke a positive, a negative or neutral emotion for training data. Hence, it is best for us to look at document level classification. Each hotels review was annotated as polarity and their aspects. And then, this system will train the reviews of the annotated corpus with word2vec and build a word embedding model. Table 2 shows the example reviews with associated sentiment classes.

Table 2: Example Reviews with Associated Sentiment Classes

Reviews	**Class Label**
ဟိုတယ် ဝန်ထမ်းလေးများအားလုံးကျေးဇူးတင်ပါတယ်. စိတ်ချမ်းသာစွာနဲ့တည်းခိုခဲ့ရပါတယ်. ဝန်ဆောင်မှုကောင်းပြီး၁၂ရက်လုံးအရမ်းအဆင်ပြေခဲ့ပါတယ်	Positive
အာရှမှာ မြင်ဖူးသမျှ ဟိုတယ်တွေထဲမှာ အကောင်းဆုံး၊ ယဉ်ကျေးသိမ်မွေ့တဲ့ ဝန်ထမ်းတွေ၊ အခန်းသန့်၊ မနက်စာကောင်း၊ လေဆိပ်နီး၊ အကောင်းဆုံးဈေးနှုန်း။ အားလုံးကို အကြံပြုလိုက်ပါတယ်နော်။	Positive
အရမ်းဆိုးတဲ့ဟိုတယ်ပါ အစားအသောက်တော့လူလိုကျွေးသင့်ပါတယ်	Negative
လေအေးပေးစက်ကမကောင်း အိမ်သာရေချိုးခန်းက ညစ်ပတ်သိုးနံ့တောင် ထွက် ရေချိုးခန်းလိုက်ကာဆို အကွက်တွေနဲ့ မီးကတအားမှိန် တခန်းလုံး ဆေးလိပ်နံ့တွေချည်း စောင်တွေကလည်း အကွက်တွေနဲ့ တာဝန်ယူမှုလည်း မရှိ	Negative
ဂုဏ်ယူပါတယ် ကံကောင်းပါစေ။ ရှေ့နှစ်မှာ ချမ်းသာပါစေလို့ ဆုတောင်းပါတယ်။	Neutral

5.6. Create Word Embedding Model

Training a neural network to discover continuous vector representations for words based on their context in a given dataset is the first step in creating a word embedding model. Word2Vec is a well-liked word embedding system that features two models: Skip-gram and Continuous Bag of Words (CBOW). The primary goal of the word embedding model is to transform words into numerical vectors. Since most deep learning architectures and machine learning algorithms are unable to handle strings or plain texts in their raw form, word embedding is necessary.To learn word embedding, there are multiple models available. They are Word2Vec, co-occurrence matrix, count-vector, and tf-idf vectorization. The Continuous Bag of Words Model and the Skip Gram Model are the most widely used model designs in Word2Vec. Skip Gram can represent for uncommon words or phrases and operates on tiny amounts of training data. In comparison to the skip gram model, the continuous bag of words model is faster, can train on a larger quantity of data, and has marginally better accuracy for frequently occurring words. This system works on Continuous Bag of Words Model in this proposed system.Several methods have been attempted to achieve word embedding on text documents. Numerous scholars and data scientists have continuously proposed different methods for processing and presenting text content. The two most popular methods for targeting documents syntactically are term frequency, or inverse document frequency (TF-IDF), or bag of words (BOW). However, these features give very little flexibility in terms of synonyms or terminology and are frequently not very effective for numerous use cases. These methods have major limitations since they are unable to fully capture the meaning of individual words as NLP develops and grows.

5.7. Word Mover's Distance (WMD)

A way to gauge how different two text documents are from one another is to use Word Mover's Distance (WMD). It considers both the "transportation cost" of transporting one set of word vectors to another and the "distance" between words in the vector space (usually using word embedding). The documents are regarded as being more comparable the lower the WMD. WMD makes use of the output of cutting- edge embedding methods like as word2vec and Glove, which provide word embedding of previously unheard-of quality and scale organically to very huge data sets. These embedding methods show that vector operations on word vectors frequently preserve semantic links.According to Word Mover's Distance (WMD), there may be some semantic significance to the distances between embedded word vectors. It considers text documents as a weighted point cloud of embedded words by utilizing this feature of word vector embedding. The minimal cumulative distance required for words from text document A to precisely match the point cloud of text document B is used to calculate the distance between the two text documents, A and B. While the earlier methods focus on either semantic or syntactic word embedding. Word Mover's Distance is a syntactic and semantic approach to measure text document similarity. The minimum distance that embedded words in one document must "travel" to reach embedded words in another document is known as the WMD distance, and it is used to measure the dissimilarity of two text documents.There are several intriguing features in the WMD distance. It achieves great retrieval accuracy by inherently incorporating the knowledge represented in the word2vec / glove space. It is easy to use and comprehend, and it is free of hyper parameters. It is very interpretable because the sparse spacing between a few individual words can be used to explain the distance between two publications. The minimum (weighted) cumulative cost needed to transfer every word from one document to the other is represented by WMD, which is the distance between the two documents. To compute the distance, solve the following linear programming issue.

$$\sum_{j=1}^{n} T_{ij} = d_{i,} \quad \forall i \in \{1, \dots, n\} \qquad (1)$$

$$\sum_{i=1}^{n} T_{ij} = d'_{j}, \ \forall j \in \{1, \dots, n\} \qquad (2)$$

$$WMD_{ij} = \min_{T \geq 0} \sum_{i,j=1}^{n} T_{ij} c(i, j) \qquad (3)$$

Where;

T_{ij} denotes how much of word i in document d travels to word j in document d;

c(i, j) denotes the cost “travelling” from word i in document d to word j in document d; here the cost is the words’ Euclidean distance in the word2vec embedding space;

If word i appears ci times in the document d, denote

$$di=\frac{ci}{\sum_{j=1}^{n} cj} \qquad (4)$$

6. Experimental Results

For the evaluation analysis, the collected data 16218 reviews which included 13344 positive, 2144 negative, 728 neutrals are used. The following confusion matrix are evaluated using the collected data based on the TP (true positive), TN (true negative), FP (false positive) and FN (false Negative).

In table 3, the actual result and prediction result are analyzed. In this proposed system, 70% of collected data are used as the training dataset and 30% are used for the testing data. The collected reviews data 11352 reviews are used as training data and 4866 reviews are defined as test data.

Table 3: Actual and Prediction Analysis Result

	Actual			
Predict		Positive	Negative	Neutral
	Positive	12524	36	67
	Negative	104	1888	42
	Neutral	720	226	622

The performance accuracy of this system is measured using Precision, Recall and F-measure. In the context of Myanmar lexicon-based sentiment analysis on hotel reviews, precision measures the accuracy of the system in correctly identifying positive or negative sentiment expressions in the reviews. It is calculated as the ratio of true positive predictions to the total number of positive predictions made by the system. A high precision indicates that the system accurately identifies positive or negative sentiment expressions in hotel reviews.

Recall in this context measures the coverage or completeness of the positive or negative sentiment expressions identified by the sentiment analysis system. It is calculated as the ratio of true positive predictions to the total number of actual positive or negative sentiment expressions in the hotel reviews dataset. A high recall indicates that the system can identify most of the positive or negative sentiment expressions in the hotel reviews.

F-measure, also known as the F1 score, is the harmonic mean of precision and recall. It provides a balanced assessment of the sentiment analysis system's performance, taking into account both precision and recall.

When evaluating the performance accuracy of a Myanmar lexicon-based sentiment analysis system on hotel reviews, it's essential to consider the nuances of the Myanmar language and the specific characteristics of hotel reviews. Additionally, the lexicon used for sentiment analysis should be tailored to capture the sentiment expressions commonly found in hotel reviews in Myanmar. Evaluating precision, recall, and F-measure helps assess the system's effectiveness in understanding and accurately classifying sentiment expressions in this specific domain and language context. These performance analyses are shown in table 4. The overall accuracy of this system is nearly 93%.

Table 4: Performance Analysis

	Precision	**Recall**	**F-measure**
Positive	0.9923	0.9382	0.9645
Negative	0.9291	0.8805	0.9042
Neutral	0.3979	0.8571	0.5435

7. Limitations of Proposed System

There are several limitations to consider when applying a Myanmar lexicon-based sentiment analysis approach to hotel reviews:

The effectiveness of lexicon-based sentiment analysis heavily relies on the comprehensiveness and accuracy of the lexicon used. Creating a comprehensive lexicon for the Myanmar language that covers all possible sentiment expressions related to hotel reviews may be challenging. Hotel reviews often contain context-dependent language and nuanced expressions that may be challenging for lexicon-based approaches to interpret accurately. Words or phrases that have different meanings in different contexts can lead to misclassification of sentiment. Lexicon-based approaches may struggle to handle negation and sarcasm effectively. In hotel reviews, guests may use negations or sarcastic language to express sentiments contrary to the literal meaning of the words, leading to misclassification.

Lexicon-based sentiment analysis models trained on general corpora may not perform well when applied to specific domains such as hotels. Hotel-related sentiment expressions, idioms, or terminology may not be adequately represented in the lexicon, leading to lower accuracy. Sentiment analysis is inherently subjective, and individuals may express different sentiments towards the same aspect of a hotel experience. Lexicon-based approaches may struggle to capture the variability in opinions and sentiments expressed in hotel reviews accurately.

The Myanmar language may exhibit regional variations, dialects, or colloquialisms that are not accounted for in the lexicon. Sentiment expressions may vary across different regions or cultural backgrounds, leading to inaccuracies in sentiment analysis. Addressing these limitations may require a combination of approaches, including improving lexicon coverage through manual curation or crowdsourcing, incorporating machine learning techniques to capture context and nuances, and domain-specific adaptation of sentiment analysis models. Additionally, ongoing refinement and evaluation of the sentiment analysis system based on real-world feedback and data are crucial for improving accuracy and effectiveness.

8. Conclusion

In summary, the proposed system can solve the complex and important area of research that has significant implications for various fields such as marketing, customer feedback analysis, and social media monitoring. This system involves several steps, including data collection and preprocessing, lexicon creation, annotation, feature selection, model training and evaluation, and experimentation with feature reduction techniques. Myanmar lexicon-based sentiment analysis on social media is challenging endeavor that can have a significant impact on the field of natural language processing and sentiment analysis. The approach for sentiment analysis of texts written in Myanmar is changing to take into account the unique linguistic and cultural quirks of the language. Despite obstacles, the convergence of specialized resources, community initiatives, and machine learning models is opening doors for insightful work in a variety of fields, including politics and business.

References

[1] M.G.V. Nunes and L. V. Avanc, "Lexicon-based Sentiment Analysis for Reviews of Products in Brazilian Portuguese,", Conference of Intelligent Systems in Brazilian, 2014.

[2] A. Levchik and N. Loukachevitch, "Creating a General Russian Sentiment Lexicon", ICLRE conference, 2016.

[3] T. T. Zin and et al., "Domain-Specific Sentiment Lexicon for Classification", ICAIT, Myanmar, November, 2017.

[4] W. W. Thant and K. Shirai, "Automatic Acquisition of Opinion Words from Myanmar Facebook Movie Comments", LREC Workshop, Miyazaki, Japan, May 7, 2018.

[5] Y. M. Aye and S. S. Aung, "Senti-Lexicon and Analysis for Restaurant Reviews of Myanmar Text", IJAEMS, Vol. 4, No 5, May 2018.

[6] C. C. Hnin and N. Naw, "Aspect Level Opinion Mining for Hotel Reviews in Myanmar Language", IEEE – ICA, July 2018.

[7] T. Yu and K. T. Nwet, "Automatic Sentiment Analysis System for Myanmar News", ICCA, Myanmar, February, 2019.

[8] W. W. Thant and E. E. Mon, "Analyzing Sentiment of Myanmar Movie Comments Using Naïve Bayes Classifier", MURC, Yangon, Myanmar, May, 2019.

[9] B. Liu, "Sentiment Analysis and Opinion Mining, Morgan & Claypool Publishers", 2012.

[10] F. Frasincar and K. Schouten "Survey on Aspect-Level Sentiment Analysis", IEEE , January , 2015.

[11] M. S. Phyu and K. T. Nwet, "A Study on a Joint Deep Learning Model for Myanmar Text Classification", IEEE Conference on Computer Applications, February, 2020.

[12] N. Y. T. Thein and K. M. Soe, "Sentiment Analysis in Myanmar Language using Convolutional LSTM Neural Network", IJNLC, Vol.10, No.4, August, 2021.

[13] S. Y. Maw and M. A. Khine, "Aspect based Sentiment Analysis for tourism in Myanmar Language using LSTM", ICCA, Myanmar, February, 2019.