A sentiment analysis model of agritech startup on Facebook comments using naive Bayes classifier

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ABSTRACT

Facebook page is a tool able to generate perceptions and acceptance, and support people and investors in making business decisions. Moreover, Facebook page plays a part in engaging people in the form of a community. People share experiences and opinions toward products, services, and trends in particular periods on the Facebook page community. Regarding sentiment analysis on Facebook pages, most education and other general topics in English have only been analyzed in English. However, sentiment analysis regarding agritech startups topics in Thai language has not been done yet. This study analyzes opinions and categorizes positive and negative comments by using naive Bayes classifier to examine the sentiments and attitudes of people and investors. The results could possibly reflect the perception rate of agritech startups in Thailand and could be applied to explain attentiveness and assess people's engagement opinions. Furthermore, it could be applied in studying consumer behavior, marketing analysis, spread of information, and attitudes. The study's model is generic and could be applied in other contexts to provide insightful suggestions.

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1. INTRODUCTION

Digital information is consistently accessed at increasing rates [1]. Facebook is one of the digital platforms where people post information relating to behaviors, attitudes, and feelings. Comments on social media platforms might be useful since they may reflect social concerns, norms, trends, or opportunities in accepting or objecting [2], [3]. Therefore, there is a good opportunity to analyze comments from Facebook to gain helpful information regarding a particular context, such as the agritech startups in Thailand.

Sentiment analysis studies and analyzes people's responses and acceptance toward an entity (e.g., posts, blogs, comments, book reviews, videos) using text analysis by computational algorithms to help determine textual reactions whether they are positive, negative, or neutral [4]. Moreover, sentiment analysis can analyze or predict trends, for example, in the stock market [5], election polls [6], or in other contexts [7]. Notably, people make comments, give opinions or share their experiences regarding service and products with friends and acquaintances through an online community. Consequently, educational and business sector are interested in studying customer opinions on online platforms. Nevertheless, the surveying might take time in collecting data, and opinions might change [8].

Researchers in computer technology and smart business have raised the aforementioned concerns [8], [9]. They designed an easy and fast algorithm to collect and analyze opinions; further, it is reliable and valid in terms of processing natural language and using machine learning to gather and assess the data [4],

[10]. Word analysis is necessary and interesting in this sentiment analysis research, especially for Thai language, since it is a complex and unique language for its structures, word formations, and varieties.

Facebook is a well-known social media platform in Thailand. In 2020, it was found that Thailand was ranked 8th in spending time on Facebook, with people posting opinions and engaging in activities [11]. Facebook users include, for example, individuals, corporates, and communities from government, private sector, and civil society. The Facebook posts include political news, entertainment news, and economic news and are open for public comments. The comments are crucial in sentiment analysis because they reflect people's thoughts toward those posts.

This study focused on analyzing and classifying positive and negative comments using a Naive Bayes classifier for validity. The algorithm is fast and accurate when classifying large and complex data. Its main attribute is being condition-free, as it only requires simple word parameter training. However, it is difficult to identify and interpret the level of sentiment regarding neutral word conditions so that neutral opinions were not counted. Thus, the researchers employ this method to classify positive and negative opinions on Facebook regarding agritech startups of Thailand. Many studies shed light on sentiment analysis in Thai language on Twitter, Facebook, and other platforms. For instance, a study of sentiment analysis using deep learning techniques on Thai Twitter data [12], using sentiment analysis to analyze Thai customer satisfaction from social media [13], and sentiment analysis of Thai children's stories [14] have used Naive Bayes to explore sentiment issues.

This study analyzed comments regarding agritech startups in Thailand on Facebook pages from April 2016 to March 2021 by gathering primary posts from the specific period. Agritech startups in Thailand are one of Thailand's 4.0 policies, anticipating exponential improvement [15]. Therefore, the Facebook page is a tool for building up perceptions, acceptance, and a support systems for people and investors [1]. Additionally, the Facebook page could engage and network people in a group format to share experiences and opinions effectively, including metadata tags or hashtags [1]. Naive Bayes learning classifier is employed to determine the percentages of words expressing emotions or positive and negative feelings.

The first part of this study presents sentiment analysis principles and procedures, and the second part addresses agritech startups in Thailand. Finally, the last part reveals the findings of this study that might reflect trends, views toward policies, support, or news on agritech startups in Thailand. More importantly, the findings could identify future trends in developing agritech startups and interesting issues for investors and the government.

2. LITERATURE REVIEW

Sentiment analysis focuses on examining and evaluating positivity and negativity of public opinions, attitudes, and emotions toward a particular issue, for instance, services, products, events, or situations [16]. Furthermore, the algorithm can classify and categorize positivity and negativity, which helps make decisions [17]. Therefore, it reflects useful trends regarding attitudes and emotions of potential customers. The study employs sentiment analysis using a naive Bayes classifier for facebook comments on agritech startups in Thai language. The principles and concepts are as follows.

2.1. Sentiment analysis

Nowadays, sentiment analysis is a popular research topic in data science, computer science, and business intelligence. Many real-life and data overload problems are part of this subject matter. It is also highly challenging as a natural language processing (NLP) research topic covering many novel subproblems. Additionally, there was almost no relevant research for sentiment analysis done before 2,000 on either NLP or linguistics. This is because of the lack of availability of opinion or text in digital forms. Since the year 2,000, the field has multiplied to become one of the most active research areas in NLP [18]. It is also widely researched in data mining, recommendation systems, expert systems, and information retrieval technologies [2]. It has spread from data science to business intelligence [19]. There are mainly three methods or levels of research on sentiment analysis [2].

- Document-level [20]: analyze the overall sentiment expressed in the text and determine if the overall sentiment is positive or negative.
- Sentence level [21]: examine the sentiment expressed in sentences and determine whether each sentence expresses a positive, negative, or neutral opinion.
- Aspect level [22]: aspect level performs better when document level and sentence level analyses do not find what people liked and did not like. The aspect level is also called the feature level.

The aspect level does not work on document, paragraphs, sentences, or clauses; it directly finds the target's sentiment. The sentiment can be positive, negative, or neutral towards that specific target or entity.

Realizing the importance of opinion, targets also help us understand the sentiment analysis problem better. Another challenge is to classify opinion into two types: regular opinion and comparative opinion [19].

The sentiment analysis studies presented in the literature are embedded in several topic areas: i) Business e.g., brand reputation [23], product/service evaluation [18], consumers/patients voice [24]; ii) Politics, e.g., identifying voter mood during election [25]; and iii) Other, e.g., event monitoring, film reviews, fake (spam) reviews [26].

2.2. Sentiment analysis on Facebook

In recent times, people can understand the real-world movements by analyzing social media data (Facebook) [20]. Sentiment analysis tools have been applied to examine the relationship between the release of products, the 'discussion' online, and comments to a post or on products, with the outcome being that such data can be used to assess/predict the user opinions [21]. The sentiment analyses are about opinion or expression or imply positive or negative sentiments or emotions towards an object. So, the elements of sentiment analysis are [2], [27]: i) "Opinion" is a judgment, viewpoint, or statement about matters commonly considered subjective [28]; ii) "entity," which is news, information, topic, issue, person, organization, or event, is the target of an opinion; and iii) "subjectivity and emotions," which are the state of mind of a person and instinctive responses.

2.3. Sentiment analysis on Facebook comments in Thai language

Facebook is one of the popular social networks in Thailand, on which people share opinions, feelings, or knowledge. Therefore, Facebook status is an essential set of information in analyzing opinions and feelings. To analyze posts in Thai language, naive Bayes was employed to pool comments and classify positive or negative meaning [29]. Moreover, naive Bayes was employed to analyze reliability in facebook status. The purpose of using naive Bayes is to identify attributes between status and relation of behavior and specific feelings. However, analyzing sentiments in Thai language is complex and complicated at the language level, meaning interpretation, and the use of the language [30]. Thus, the researchers considered using naïve Bayes to ease the analysis.

2.4. Sentiment analysis using natural language processing

Sentiment analysis is natural language processing used to identify and analyze texts for whether the sentiment is positive, negative, or neutral. The analysis helps businesses or investors examine and gain a deeper understanding of customers' opinions and satisfaction, market trends, or economy [30]. Furthermore, sentiment analysis using natural language processing and computing algorithms can simulate the sentiment analysis models [31]:

- Rule-based: the system automatically performs sentiment analysis based on a set of manually crafted rules. These rules may include various NLP techniques developed in computational linguistics: stemming, tokenization, part-of-speech tagging and parsing, and lexicons (i.e., lists of words and expressions).
- Automatic methods: contrary to rule-based systems, these do not rely on manually crafted rules but on machine learning techniques. A sentiment analysis task is usually modeled as a classification problem, whereby a classifier is fed a text and returns a category, e.g., positive, negative, or neutral.
- Hybrid systems: combine the desirable elements of rule-based and automatic techniques into one system. One huge benefit of these systems is that the results are often more accurate.

2.5. Sentiment analysis using Naive Bayes classifier

Many studies with machine learning algorithms have used sentiment or opinion mining. Some common algorithms used in sentiment analysis are naïve bayes, maximum entropy, and support vector machine [2], [29]. Naive Bayes classifiers are highly scalable and require a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression, which takes linear time rather than an expensive iterative approximation used with many other classifiers [29], as in the equation:

$$P\ (A|B) = \frac{P\ (B|A) * P\ (A)}{P\ (B)}$$

It was found that using a naive Bayes classifier is convenient and easy to do for word training, especially for word features with large data sets to analyze and classify. In addition, it can be used to develop complicated models. However, the naive Bayes classifier only performs well when the testing attributes are independent [32]. Therefore, the researchers decided to employ this technique, because it can classify large data sets, learn with a large number of inputs, and analyze the data in various ways. Thus, because the collected large data sets are complicated and contain independent attributes, the researchers decided to use naive Bayes classifier as the primary approach in this study.

2.6. Agriculture startups in Thailand

The startups and enterprises are important contributors in the national economy, the country's lifeblood, and flexibly adapt to the circumstances; these are primary mechanisms in an economic recovery and strengthen economic progress with increasing employment in society [33]. Moreover, agriculture startups have become the training centers for workers who can gain real work experiences [34]. In addition, they are starting points of product innovation and various types of services. People who are interested in investing in startups and enterprises prefer lower capital and risk than in investing in large industries [33], due to connecting networks and joint investments with large corporations or other related businesses. Additionally, they create value for raw materials because they use domestic resources mainly generating income for the country, directly in the agriculture, in manufacturing for export, and in the tourism sector [35]. Startups also prevent monopoly formation in the economy, strengthen fair competition, and force efficiency of the overall economy. More importantly, it would be beneficial to identify future trends in developing agritech startups and interesting issues for investors and the government.

3. RESEARCH METHOD

This research applies a naive Bayes classifier to analysis of Facebook comments on agri-tech startups, in Thailand. The researchers setting the process steps are: finding data, data collection, data selection, data cleaning, data classification, and presentation of output. The research scheme is summarized in Figure 1.

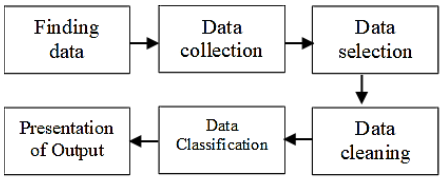

Figure 1. Research method

a. Finding data: the researchers searched for posts related to the agritech startups, in Thai language on Facebook, using these keywords: agritech startups, startups, and startup business. The result was that there were 12 posts from April 2016 to March 2021.
b. Data collection: the researchers used export comments software to gather the comments of the 12 posts. There were 1,001 comments in total, classified as in Table 1.
c. Data selection: the researchers selected relevant data by skimming.
d. Data cleaning: the researchers eliminated redundant, irrelevant, and incomplete comments, including tagging, pictures, and emoji icons. After cleaning, there were 405 comments as shown in Table 2.
e. Data classification: the researchers used the model training of Naive Bayes classifier algorithm, a binary sentiment analysis in Python from Abromberg [36], to analyze and summarize the comments in Thai language. The process is schematically shown in Figures 2 and 3.

Table 1. Comment classification

Post Name/Topic	Comment Count
The prime minister and faculty visited the digital economy promotion agency	159
All Asian countries go to agritech startups	27
Startup greenhouse	132
Only 10k for a smart farm!!	97
Traditional farmers might work harder	30
StartUp! Use leaves to make containers	34
Listenfield: algorithm helps to form a new agriculture	60
Digital startup exhibition (digital Thailand big bang: digital station)	286
Startup, homegrown vegetable in container carriers	86
Containers from leaves	11
Soil scanner	29
Chula startup, Covid-19 vaccine from protein in tobacco leaves	50

Table 2. Data after cleaning

Post Name/Topic	Comment Count
The prime minister and faculty visited the digital economy promotion agency	61
All asian countries go to agritech startups	19
Startup greenhouse	43
Only 10k for a smart farm!!	41
Traditional farmers might work harder	16
StartUp! Use leaves to make containers	27
Listenfield: algorithm helps to form a new agriculture	26
Digital startup exhibition (digital Thailand big bang: digital station)	84
Startup, homegrown vegetable in container carriers	40
Containers from leaves	9
Soil scanner	17
Chula startup, Covid-19 vaccine from protein in tobacco leaves	22

f. Presentation of output: the outputs are

1) Showing positive and negative comments as integer counts and percentages: i) pos=xxxx, ii) neg=xxxx, iii) pos=xx.xx %, and iv) neg=xx.xx %
2) Showing positive and negative comments from keyword search: i) text: xxxx, ii) test_sent: xxxx, and iii) tag: xxxx (pos or neg)

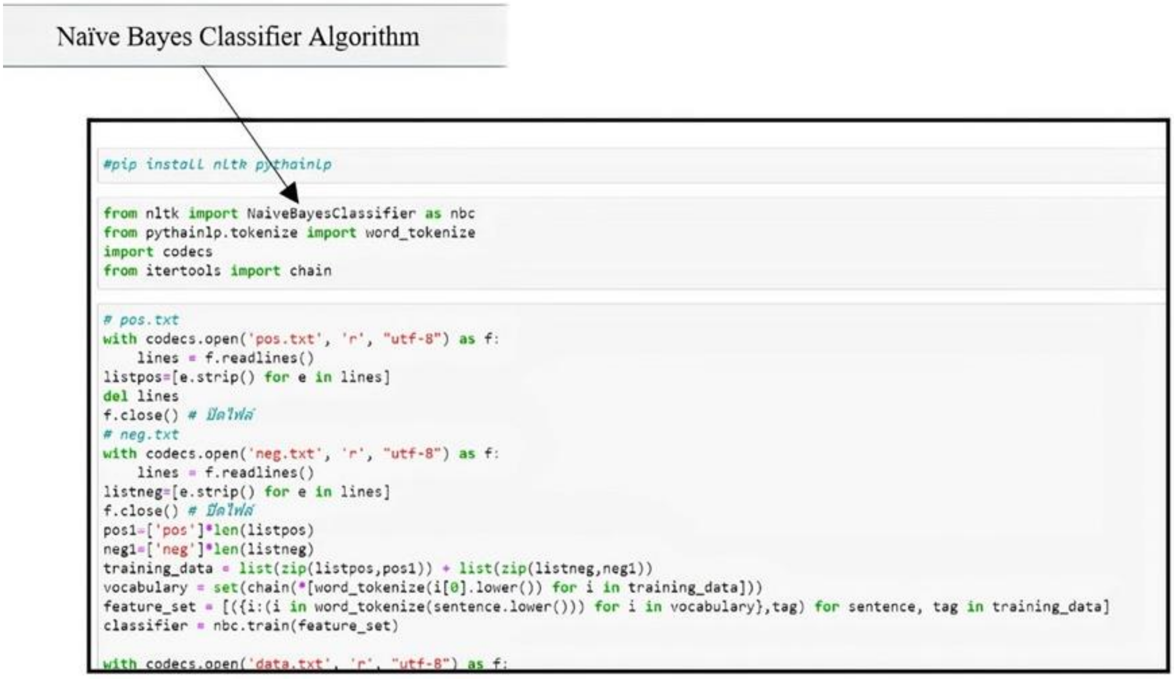

Figure 2. Illustrates the use of the algorithm to classify Facebook comments on agritech startups in Thailand

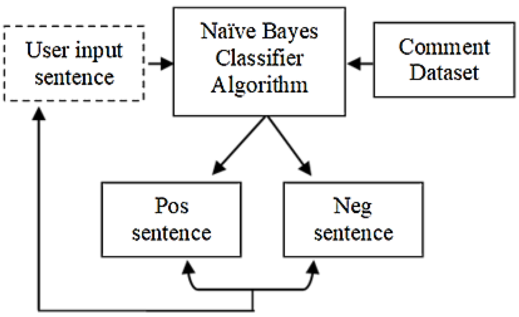

Figure 3. Sentiment analysis process

4. RESULTS AND DISCUSSION

According to the sentiment analysis findings, most comments showed positive results related to Thailand 4.0 [15] and policy of supporting Thai startups to strengthen the business sector's competitive level [34]. Most sentiment analysis results reveal positive trends that identify the interests and acceptance of people and investors regarding agritech startups. Thus, overall, the results show people's interests in agritech startups in Thailand and can be used to study further consumer behavior, marketing analysis, product designs, trends, and attitudes. To classify Thai language comments in positive and negative statements, the researchers did classify comments and comments separated by post topic.

4.1. Classify comments

The 405 comments were classified as follows. Showing positive and negative comments as integer count and percentage, shown in Figure 4, pos=258 (63.7%) and neg=147 (36.3%). In the analyzed data, there were 258 positive comments and 147 negative comments. In other words, the commenting people had more positive emotions (63.7%) than negative emotions (36.3%) towards the issue as shown in Figure 5 and Figure 6. Showing positive and negative comments from keyword search as shown in Table 3.

```
    lines = f.readlines()
listneg=[e.strip() for e in lines]
f.close() # ปิดไฟล์
pos1=['pos']*len(listpos)
neg1=['neg']*len(listneg)
training_data = list(zip(listpos,pos1)) + list(zip(listneg,neg1))
vocabulary = set(chain(*[word_tokenize(i[0].lower()) for i in training_data]))
feature_set = [({i:(i in word_tokenize(sentence.lower())) for i in vocabulary},tag) for sentence, tag in training_data]
classifier = nbc.train(feature_set)

with codecs.open('data.txt', 'r', "utf-8") as f:
    read_data = f.readlines()
pos=0
neg=0
for i in range(len(read_data)):
    test_sentence = read_data[i]
    featurized_test_sentence =  {i:(i in word_tokenize(test_sentence.lower())) for i in vocabulary}
    tag=classifier.classify(featurized_test_sentence)
    if(tag=='pos'):
        pos+=1
    else:
        neg+=1

posPer=((pos/len(read_data))*100)
negPer=((neg/len(read_data))*100)
print("pos = ",pos)
print("neg = ",neg)
print("pos = ",round(posPer,2),"%")
print("neg = ",round(negPer,2),"%")
```

Figure 4. Code sample to classify positive and negative comments as integer count and percentage

```
ข้อความ : สาธุ
test_sent: สาธุ
tag: pos

ข้อความ : ดีใจ
test_sent: ดีใจ
tag: pos

ข้อความ : ศรัทธา
test_sent: ศรัทธา
tag: pos

ข้อความ : สวรรค์
test_sent: สวรรค์
tag: pos

ข้อความ : ตายแน่
test_sent: ตายแน่
tag: neg

ข้อความ : เสียใจ
test_sent: เสียใจ
tag: neg
```

Figure 5. A sample of classifying positive and negative comments

```python
while True:
    test_sentence = input('\nข้อความ : ')
    featurized_test_sentence =  {i:(i in word_tokenize(test_sentence.lower())) for i in vocabulary}
    print("test_sent:",test_sentence)
    print("tag:",classifier.classify(featurized_test_sentence)) # ใช้โมเดลที่ train ประมวลผล
```

Figure 6. Code sample of classifying positive and negative comments in keyword search format

Table 3. Overall sentiment analysis

	Comment Count	Pos Sentiment	Neg Sentiment
Comments Source	405 (100%)	258 (63.7%)	147 (36.3%)

According to the output, the researchers determined F-measure, precision, recall, and accuracy listed in Table 4. Table 4 shows the effectiveness of the method in gathering and analyzing data. In this case study, F-measure was 88.00%, precision was 85.00%, recall was 92.00%, and accuracy was 79.00%. Overall, the researchers found that F-measure was 75.00%, precision was 80.00%, recall was 75.00%, and accuracy was 61.00%. This shows that some comments had slang or ill-structured phrases, which affected the word analysis algorithm [37].

Table 4. Classifying comments by F-measure, precision, and recall

Post name/topic	F-measure	Precision	Recall	Accuracy
The prime minister and faculty visited the digital economy promotion agency	71.00%	67.00%	75.00%	55.00%
All asian countries go to Agritech startups	80.00%	83.00%	77.00%	67.00%
Startup green house	67.00%	100%	50.00%	50.00%
Only 10k for a smart farm!!	78.00%	100%	64.00%	64.00%
Traditional farmers might work harder	71.00%	85.00%	61.00%	55.00%
Startup! Use leaves to make containers	74.00%	78.00%	70.00%	58.00%
Listen field: algorithm helps to form a new agriculture	75.00%	67.00%	86.00%	60.00%
Digital startup exhibition (digital Thailand big bang: digital station)	77.00%	65.00%	96.00%	63.00%
Startup, homegrown vegetable in container carriers	55.00%	50.00%	60.00%	38.00%
Containers from leaves	83.00%	100%	89.00%	74.00%
Soil scanner	88.00%	85.00%	92.00%	79.00%
Chula startup, Covid-19 vaccine from protein in tobacco leaves	84.00%	80.00%	89.00%	73.00%
Overall	75.00%	80.00%	75.00%	61.33%

4.2. Comments separated by post topic

Table 5 reveals that most of the comments were positive except for some comments in a digital startup exhibition (digital Thailand big bang: digital station). However, it contained negative comments since the content was irrelevant to the startups. Figure 7 shows the percentages of sentiment analysis, where positive sentiment (63.70%) was more prevalent than negative sentiment (36.30%).

Table 5. Sentiment analysis by post name/topic

Post name/topic	Comment count	Pos sentiment	Neg sentiment
The prime minister and faculty visited the digital economy promotion agency	61 (100%)	37 (60.66%)	24 (39.34%)
All Asian countries go to Agritech startups	19 (100%)	16 (84.21%)	3 (15.79%)
Startup green house	43 (100%)	26 (60.47%)	17 (39.53%)
Only 10k for a smart farm!!	41 (100%)	29 (70.73%)	12 (29.27%)
Traditional farmers might work harder	16 (100%)	14 (87.5%)	2 (12.5%)
Startup! use leaves to make containers	27 (100%)	17 (62.96%)	10 (37.04%)
ListenField: Algorithm helps to form a new agriculture	26 (100%)	17 (65.38%)	9 (34.62%)
Digital startup exhibition (digital Thailand big bang: digital station)	84 (100%)	35 (41.67%)	49 (58.33%)
Startup, homegrown vegetable in container carriers	40 (100%)	29 (72.5%)	11 (27.5%)
Containers from leaves	9 (100%)	8 (88.89%)	1 (11.11%)
Soil scanner	17 (100%)	14 (82.35%)	3 (17.65%)
Chula startup, COVID-19 vaccine from protein in tobacco leaves	22 (100%)	16 (72.73%)	6 (27.27%)

Applications of this study: the application of sentiment analysis in practice regarding the government and business sector was demonstrated. The case study focused on a policy of supporting and developing agritech startups or related social trends. Further, the findings could be applied in a marketing context, such as assessing customer and entrepreneur behaviors and perceptions, future markets and business trends, needs, and people's problems expressed in Facebook comments. Thus, sentiment analysis helps summarize the people's views in a particular context as in explaining marketing phenomena, sales strategies, attitudes, and behaviors of consumers. In the same way, sentiment analysis reflects the effectiveness of the government's policy on applying it into practice. Novelty/originality of this study: the approach demonstrated could be applied in studying consumer behavior, marketing analysis, spread of information level, and attitudes. The study's model can be used in other cases to provide insightful suggestions.

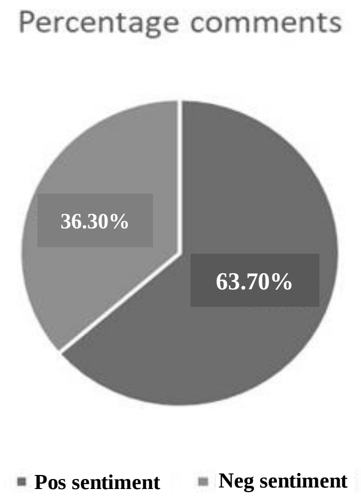

Figure 7. Percentages of sentiments in posted comments on agritech startup topics

5. CONCLUSION

This study used the naive Bayes classifier algorithm in binary sentiment analysis with python to analyze Thai Facebook comments regarding feelings toward posts of agritech startups in Thailand. We found that there were positive and negative feelings, but positive comments were more frequent. However, some words were slang or unstructured and not possible to analyze using the model, so the researchers eliminating them at the stage of data selection and data cleaning to reduce errors in the results. In further research, we would adjust the accuracy of classifying comments or data on feelings from key informants. Consequently, the algorithm will be able to analyze words and phrases more accurately in Thai language. The findings could be used in marketing analysis or for national strategy and policy, such as exploring attitudes, opinions, openness, acceptance, responses to new information, or engagement to benefit the government, business sector, and the people.

Besides, the sentiment analysis showed that most comments were positive (63.70%). This reflects people and domestic investors' positive interests, acceptance, attitudes toward agritech startups that are new and trendy. People pay attention to this trend even the startups are based on knowledge of technology and innovation. It was also found that these positive reflections reveal a level of perception and attentiveness toward agritech startups in Thailand, even though it is for specific groups. Moreover, the positive views also show good engagement and creative critiques.

In contrast, negative comments were 36.30%. It might be a view related to temporary businesses. A large sum of investment funds is another factor driving Agritech startups besides technology, innovation, and knowledge. Therefore, this factor might affect people's opinions negatively. However, the study will be the foundation for assessing agritech startup trends in Thailand, such as consumer behavior and marketing analysis.

Limitations of this study: regarding the search and collection of Facebook posts, the limitations are as follows: i) there was a small number of agritech startup related posts because this is a niche market and too specific, so not many people are interested; and ii) since it is too specific and it is in Thai, engagement rate is low compared to English or Chinese language posts further research: the researchers plan to use sentiment analysis to determine agritech startup entrepreneurs' opinions in southern Thailand in combination with in-depth interviews. The second phase is to analyze in-depth opinions regarding the use of technology to inspect agritech startups and factors influencing the success of using technology.

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