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Exploring Customer Review of Local Agriculture Product Acceptance in Malaysia: A Concept Paper on Sentiment Mining

Zaireen Abdul Rahman[1], Bazilah A. Talip[1]*, Husna Sarirah Husin[2]
[1] Malaysian Institute of Information Technology (MIIT), Universiti Kuala Lumpur (UniKL), 50250 Kuala Lumpur, Malaysia
[2] School of Computer Science Taylor's University, 47500 Subang Jaya, Selangor, Malaysia

*Corresponding author: bazilah@unikl.edu.my
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Abstract— Online consumer reviews in e-commerce are one technique to gather consumer opinion and sentiment about a company's products and services. However, manual analysis is impractical due to natural language text's enormous volume and complexity. Text mining and sentiment analysis methods based on machine learning provide an opportunity to analyze data for marketing objectives by increasing sales, positive electronic word-of-mouth (e-WOM), and meeting consumer demands and wants through the enhancement of market offerings. Despite the numerous benefits of analyzing e-commerce reviews to assist a company's marketing strategy, very little research has focused on sentiment and acceptance for Malaysia's local agriculture products due to mixed language (English-Malay language) processing challenges. This concept paper highlights the use of text mining techniques to extract valuable insights from e-commerce comments related to Malaysian local agriculture products. By leveraging text mining, the study aims to better understand consumer sentiments, preferences, and feedback regarding local products, thereby facilitating improved market analysis and decision-making processes.

Keywords— sentiment mining, preferences, acceptance, Malaysia agriculture products, online review.

I. Introduction

Consumers' feedback on online platforms is considered electronic word-of-mouth (eWoM) in the new participatory culture, alongside blogs, forums, social media, videos, photo sharing, and viral marketing [1]. Traditionally, word-of-mouth (WoM) spreads when a consumer buys a product and tells their friends and family about it. Companies seeking consumer feedback must collect data through face-to-face, telephone interviews, focus groups, mail surveys, opinion polls, observational studies, and online research [2] in order to improve product sales with positive reviews by meeting consumer needs [3]. However, with the current trend of social media, eWOM is gaining popularity since consumers share their opinions online and this review is used by new clients.

Analyzing online consumer evaluations can have a big impact on the company and potential buyers. According to [4], a summary statistic on internet reviews shows that 9 out of 10 individuals (89%) read reviews before purchasing a product [5], particularly for intangible things. 4 out of 5 consumers (79%) believe that what they read online is similar to personal recommendations from relatives and friends [6]. 62% will not purchase from companies that remove negative evaluations [5]. Before purchasing a product, 54.7% of consumers read more than four reviews [7]; 47% post comments online each month [8]; 53% of consumers expected organizations to respond to critical comments within a week, whereas 1 in 3 expected responses within 3 days [9].

Sentiment mining have been applied in the variety of industries such as banking, customer service, healthcare, government sectors, stock analysis, market research, hospitality industry and many more. Below is an example taken from Repustate company in resolving issues for their clients internationally [10].

Fig. 1 Sentiment mining on real-world use case

Feedback is important for businesses for a variety of reasons, including improving products and services, innovating to higher quality standards, refining flaws if any

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from consumer complaints, measuring consumer expectations of a value delivered [11], engaging in consumer relationships, producing consumer loyalty to the brand, eventually leading to repeat purchases, spreading a positive word of mouth to other potential consumers, and it helps the company [12]. As more people are given space and platforms to create user-generated content (UGC) and consumers trust more in UGC than corporate advertisement [13] data becomes overwhelming and it is impossible to analyse manually because it is labour-intensive and expensive. It is irrelevant to collect large amounts of data without making it understandable. In businesses, data mining and sentiment analysis from consumer feedback after purchasing is important to increase sales volume and revenues [3], reduced costs, market research, detect the pattern, trend analysis, target consumer needs, target promotion, advertisement, and predict market response to succeed in today's business environment. Nevertheless, only a handful of Malay sentiment mining studies have been carried out.

II. Problem Issues and Statement

The lack of sentiment analysis feedback for agriculture products via online reviews in Malaysia's e-commerce sector is a serious issue. Farmers, sellers, and consumers struggle to gauge overall satisfaction, sentiment, and user experiences connected with agriculture products available online without effective sentiment analysis. The GDP contribution of Micro, Small & Medium Enterprises (MSMEs) to the agriculture sector in 2021 was 10.5% [14]. The online agriculture products market is anticipated to expand at a compound yearly growth rate of 6.0%, from US$ 9,714.6 million in 2021 to US$ 17,308.3 million in 2031 [15]. The E-Commerce Agricultural Products market is projected to reach USD 50.5 billion by 2028, growing at a compound annual growth rate (CAGR) of 6.94% from its estimated USD 33.8 billion in 2022 [16]. Revenue growth for this target market is anticipated to be fueled by increased investments in agricultural infrastructure and the implementation of various government initiatives in countries like China, India, and others. This can be increased by considering the analysis of consumers' needs and wants through online comments. Successful decision-making is hindered due to the absence of sentiment analysis feedback, which limits the ability of stakeholders such as manufacturers and government to evaluate product quality, dependability, and suitability through the experiences of others, impacting their decision-making process significantly. As a result, this issue affects consumer trust, consumer retention, stifles market growth, and limits the potential of Malaysia's agriculture products e-commerce industry. Addressing this issue is critical if the government and companies are to deliver accurate and meaningful feedback, boost consumer confidence, and foster the establishment of a robust online marketplace for agriculture products.

Online review written in Malaysia's e-commerce usually is a mixture language usually in English and Malay. [17] researched on food preference, [18] examined star rating on restaurants, [13] studied incentive hierarchies affect user behaviour, [19] compared China and USA tourist satisfaction in a restaurant, and many studies are being conducted to improve algorithm accuracy [20]–[25]. Other than English, most research has been conducted in Arabic [26]–[29]; French language [30]–[32]; Chinese language [33]–[35] and Italian [36]–[38]. On the contrary, in Malay language there are not much research especially in processing a text mixture English and Malay language simultaneously. This study endeavours to overcome the challenges associated with processing mixed language comments in English and Malay to analyse consumer comments from e-commerce platforms and assess the acceptance of agriculture products in Malaysia.

Therefore, this conceptual paper aims to explore and identify the key factors that influence consumer's sentiment and preference in online reviews of agricultural products, aiming to understand what aspects of these reviews are most influential in shaping consumers' perceptions and purchasing decisions.

III. Significance of The Research

This study aims to analyse feedback on agricultural products through online reviews in the e-commerce sector, which holds significant relevance and importance for several reasons. Firstly, it addresses the critical need to enhance transparency and consumer confidence in Malaysia's online agricultural product trade. By conducting a thorough examination of online evaluations, this study can provide valuable insights into the quality, authenticity, and suitability of agricultural products, enabling consumers to make well-informed purchasing decisions.

Secondly, the findings of this study have the potential to contribute to the overall growth and development of Malaysia's agriculture e-commerce business. By identifying areas for improvement and highlighting best practices, the study can offer guidance for enhancing the industry. Moreover, leveraging technology can empower farmers and sellers to understand customer preferences and adapt their products accordingly, fostering a more competitive and prosperous environment.

Thirdly, it can be impactful for the stake holders. Manufacturers can utilize this data to enhance product quality, identify opportunities for innovation, and tailor their marketing strategies to better meet consumer needs. By gaining a deeper understanding of market trends, suppliers can optimize their supply chain for efficient distribution and inventory management. The government can also utilize this information to address consumer concerns, make well-informed policy decisions, and effectively regulate the industry.

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This study contributes significantly to the body of knowledge by adding new valuable insights into consumer preferences, attitudes, and behaviours towards agricultural products by unravelling the perception consumers focusing in agriculture products in Malaysia through analysing text mining in online review fulfilling the research gap. The outcome of a new proposed conceptual model of acceptance agriculture products can be transferable to other countries to shape their local products to reach globally. From a methodological point of view helps researchers as a guide to analyze data using novel data sources from online reviews in multilingual language (English-Malay language) using state-of-art BERT algorithm could contribute to analyzing consumers comments compared to traditional research methods. It it offers a real-time and cost-effective method to gather large-scale data on consumer opinions and experiences, enabling researchers to analyse trends and patterns across diverse demographics and geographic regions.

Furthermore, such research contributes to a better knowledge of how cultural influences, language nuances, and ethnocentrism influence product acceptability, resulting in more effective cross-cultural marketing practises. This research's findings can help optimise product development, pricing, and communication strategies, supporting innovation and competition in the agriculture industry. Furthermore, it adds to the larger field of consumer behaviour, digital marketing, and e-commerce, broadening the collective knowledge base and informing future research in related domains. In conclusion, mining online consumer reviews for agricultural products enables stakeholders to make data-driven decisions, enhance consumer satisfaction, and support a flourishing and sustainable agricultural ecosystem.

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IV. Theoretical Overview

In this study, two underpinning theories are identified as relevant to this research, and the following subsections offer an overview of these theories. These subsections are, namely: 4C's marketing mix theory [39] and ethnocentrism theory [40]. Marketing mix theory is chosen as it could be identifying which four elements that influenced consumer in purchase agriculture products. While ethnocentrism is important as it helps researchers and businesses understand how cultural biases and preferences influence consumer behaviour and attitudes. These identified theories have been used as a lens to understand the relationship between consumer perception and acceptance towards agriculture products affected their purchasing behaviour resulted in their online review. Subsequently, helps in developing agriculture acceptance model.

A. 4C's Marketing Mix

Marketing mix is chosen as it is an integrated marketing communication model that emphasizes on customer-centred approach through four key variables: customer, cost, convenience, and communication. These variables help identify which variables are more dominant in the acceptance of agricultural products.

A marketing mix is a set of marketing strategy tools a company can do to engage with consumers and deliver and exchange offerings that has value to the consumer [11]. The 4C's marketing mix is a modern adaptation of the traditional 4P's marketing mix that takes into consideration consumers' changing demands and preferences. The 4C's concept emphasises putting the consumer at the centre of marketing strategies, understanding their wants and needs, and adjusting marketing efforts appropriately.

There are several models marketing mix that evolved over time. Refer Fig. 1. The first model was introduced by [41] has Product, Price, Place, Promotion known as 4Ps marketing mix from a managerial point of view.

Fig. 2 An improved evolution marketing mix model from 4Ps to 4Cs

It provides a framework for marketers to analyse and create their marketing strategies by taking into account various variables that contribute to the market success of a product or service.

According to the marketing mix theory, a successful marketing strategy entails finding the right balance and integrating four elements: the product itself, its price, the distribution channels used to make it available to consumers, and the promotional activities used to communicate its value and benefits.

[39], introduced the integrated 4C's marketing communication theory which emphasizes on consumer-centered marketing model namely customer, cost, convenience, and communication.

Customer - Instead of focusing on the product, it focuses on what the consumer wants. To identify consumer perception and acceptance through online reviews, businesses need to analyze the feedback provided by customers. Reviews often contain valuable insights into how consumers perceive the agricultural products, what features they value the most,

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and what improvements they would like to see. By understanding the customer's perspective through reviews, businesses can tailor their offerings to better meet customer expectations.

Cost – the price paid by the customer is only a subset of the overall cost of a product. It represents an overall cost to own the product including the delivery of the product and time to obtain the product. It represents an overall cost to own the product including the delivery of the product and time to obtain the product. In online reviews, consumers may comment on the affordability, value for money, and perceived benefits of the agricultural products. Analyzing these reviews can help businesses gauge whether the cost is aligned with the perceived value by consumers, and if adjustments are necessary to enhance acceptance.

Convenience – the ease of buying and obtaining the product. In the context of agricultural products, online reviews can provide insights into factors such as delivery speed, packaging quality, and ease of use. Positive reviews may indicate that the products are convenient to purchase and use, while negative reviews may point to pain points that need to be addressed.

Communication – a two-way interaction between the company and consumer. Online reviews serve as a channel for consumers to express their opinions, and businesses can respond to these reviews to address concerns, provide clarifications, and demonstrate a commitment to customer satisfaction. Engaging with customers through reviews can build trust and loyalty.

B. Theory Of Ethnocentrism

The term "ethnocentrism" itself was coined by [40], an American sociologist, in the early 20th century. It has been studied and discussed by scholars in the fields of social psychology, anthropology, and sociology.

The theory of ethnocentrism refers to the tendency of individuals or groups to criticise and evaluate other cultures based on their own culture's norms, values, and beliefs. It is a social psychology and anthropology concept that emphasises how people frequently regard their own culture as better or the "right" way to do things, while viewing other cultures as inferior or aberrant [42].

Ethnocentrism manifests itself in a variety of ways, including cultural stereotypes, prejudice, discrimination, and a belief in cultural superiority. It can lead to a skewed perspective in which people judge and interpret the behaviours, practises, and norms of other cultures through the lens of their own cultural framework. This can lead to misunderstandings, disputes, and an inability to appreciate or comprehend the diversity and richness of the world.

Ethnocentrism can be caused by a variety of circumstances, including a desire for social identity and belonging, a lack of exposure to different cultures, and a lack of information or understanding about cultural differences. It frequently fosters ingroup-outgroup dynamics, in which people within a culture identify strongly with their own group and see others as different or "other."

It is crucial to recognise that ethnocentrism is not always inherent or universal. It varies between persons and societies, and it is influenced by education, diversity exposure, cultural openness, and intercultural encounters. Recognising and addressing ethnocentrism is critical for establishing cultural sensitivity, respect, and peaceful intercultural partnerships. As an alternative approach, cultural relativism, which entails understanding and accepting cultural differences on their own merits, is frequently recommended.

Ethnocentrism theory remains an important subject of study and research, particularly in the domains of intercultural communication, cultural psychology, and cross-cultural studies. It contributes to understanding the dynamics of cultural biases, intergroup conflicts, and the difficulties of cultural understanding in a globalised world. It is essential in identifying consumer perception and acceptance of agricultural products through online reviews because it sheds light on how cultural biases impact consumer behaviour. Businesses can adapt their marketing tactics and product offerings to fit various cultural contexts by recognising the importance of cultural elements. In order to promote better acceptance among multiple consumer groups in the online marketplace, understanding ethnocentrism is helpful in analysing consumer preferences, addressing language and communication barriers, and adopting cross-cultural marketing strategies.

Below is the conceptual framework propose for this study.

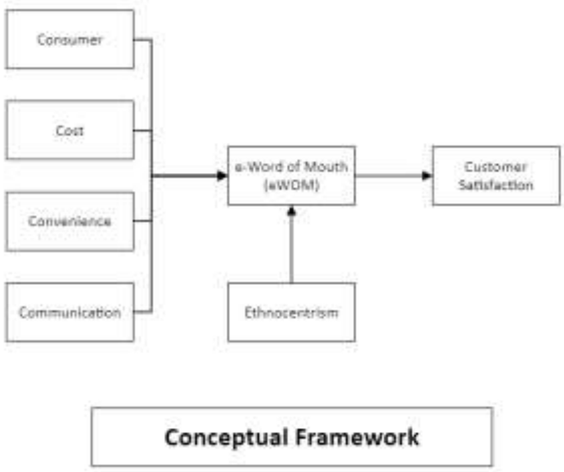

Fig. 3 Conceptual framework

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V. Discussion Of The Literature Review

A. *Online Review*

Traditional word-of-mouth has taken on a new electronic dimension thanks to the development of the Web 2.0 and the spread of web-based opinion platforms, becoming electronic WOM (eWOM). Traditionally, is considered person-to-person communication, communicators and recipients about products, services and brands [43]. Meanwhile eWOM describes by [44] as "any positive or negative statement made by potential, actual, or former consumers about a product or company, which is made available to a multitude of people and institutions via the Internet." One form of electronic word-of-mouth (eWOM) communication is online reviews aside from blogs, forums, social media, videos, photos sharing, and viral marketing in new participatory culture [1]. Online review is defined as "a review of a product or service where it reflects the opinions and experiences of a consumer purchasing a product or service" [45]. The greatest way to strategize about product and service positioning is through electronic word-of-mouth (eWOM), that has evolved into a new form of consumer opinion and feedback on the products and services that businesses offer.

The pioneer company to adopt online review function in its marketing model as web-based opinion platforms to focus on consumer-centric was Amazon by its founder, Jeff Bezos in 1995 [46]. Subsequently, 132% of profits since 2004 and currently boasts around 10 million consumer reviews across all product categories, and these reviews are one of the most popular and successful elements of Amazon.com [46], [47].

B. *Usefulness in Sales*

A few studies has examined on product online reviews translate into product sales [3], [48]–[50]. Changes in valence comments impact revenue [51]. The usefulness of online reviews has been well recognized in the literature already in existence. In the review study conducted by [52] addresses from conclusions drawn from an examination of the literature on the usefulness and implications of eWOM for marketing communications and marketing strategy.

Numerous studies showed online reviews influence sales. [53], explored importance between non-eWOM and eWOM users with sales. They are a significant relationship with sales attributes. The number of reviews produced by eWOM consumers is much higher in term of sales than the number of reviews produced by non-eWOM consumers.

This is further supported by another study by [49] wherein quality of a review subsequently has effect on sales. He identifies product sales are at their highest when positive evaluations are high and negative are at their lowest and vice versa. [50] proves positive reviews (high reviews scores, positive review sentiment and positive review title sentiment) with review scores inconsistency significant with sales. In conclusion, online reviews do impact on sales.

A study on systematic literature review was done on rating and reviews and it was determined that various review and rating factors, including volume, length, top reviewer reviews, average rating, review history, aggregate ratings, review variance, and rating ratings, all influenced by behavioral constructs, affected consumers' purchasing decisions [54]. It is proven ratings and reviews are significantly important to both businesses and customers during their purchases, but companies are losing sales, profits, and valuable information without ratings and reviews as their research demonstrated in the diagram below [55]. Similarly, results show a relationship between star rating and sentiments using deep learning via natural language processing, machine learning, and artificial neural networks [56].

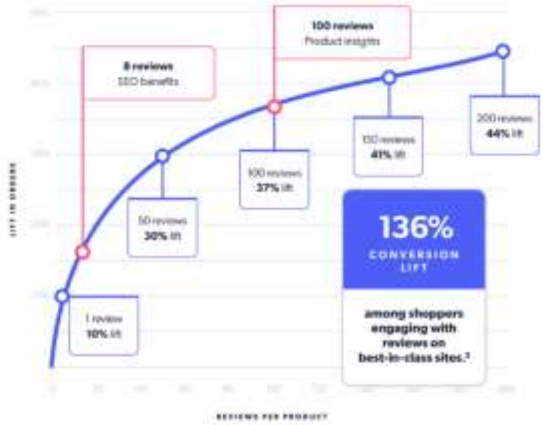

Fig. 4 The research result from [56]

C. *Impact on Purchase Behavior*

Positive or negative comments has a swaying effect on consumer buying decision who would not have made the initial purchase of the product [57].

D. *Impact of Negative Comments*

Negative or positive comments made by users make it possible for eWOM to spread like wildfire within a very short span of time is called online firestorms. It is also known as viral marketing which used interchangeably with eWOM [58]. Consequently, it is a new obstacle for marketers to manage the damage and rehabilitate reputation. Hence, company response to negative reviews faster will increase its sales [3]. Negative reviews were studied in depth by [59] while [60] encounter negative reviews deliver results that go beyond sales.

E. *Impact On Brand*

Oral communication is less powerful than online reviews of consumers' brand usage experiences in building a solid brand image [61]. A user-generated review is considered to be much more effective and credible than an effort made by a company. Numerous studies show online review significant to build brand strength and consumer loyalty. In addition,

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[61] analyse credibility online review on brand image. The result reveals, factor of reviewer and review quality have significant effect compared to review consistency and receiver in credibility aspect. In addition, credible online reviews influence hedonic brand perception more than functional brand perception. According to our research, peripheral cues like reviewer experience, product/service rating, and website reputation, as well as argument quality factors like accuracy, completeness, and quantity of online reviews, have a significant impact on the credibility of online reviews, which in turn influences consumers' purchase intentions [62].

The analysis of the literature reveals, numerous studies in sentiment analysis have been typically done in hotels and tourism area [63]–[67]. [67] explored factors of satisfaction and dissatisfaction consumers while staying in hotels from Tripadvisor using text mining. Results showed satisfied consumers usually evalute through intangible aspects such as staff friendliness while dissatisfaction consumers will complaint on tangible aspects such as furnitures, building including cost and pricing. Meanwhile, [64] studied consumer's satisfaction through online rating using machine learning method SOM and TOPSIS, an MCDM method in clustering the comments. [64] found, 5-star rating "Sleep Quality," "Location," and "Service" are the most crucial criteria, whereas for those of 4-star hotels, "Sleep Quality," "Room," and "Service" are more crucial. Then again, furnishing and cleanliness are the most crucial criteria that makes people complaints especially in luxury hotels [65]. However, unexpectedly [66] pointed out that negative comments are more useful than positive comments for their upcoming purchase decisions regarding hotel choice.

F. *Consumer Satisfaction*

Commonly, some study would consider restaurant reviews as a part of tourism and hospitality domain. [68] identifying relationship between consumers satisfaction and online reviews in restaurants. In the study, sentiment does influence consumers satisfaction. Consumer satisfaction increases with more positive comments. The result aligned with previous studies that online review influenced consumer satisfaction. However, [20] found negative emotional intensity has a negative impact on perceived review usefulness, while positive emotional intensity has the opposite effect.

[18] has introduced star ratings as an influence on restaurant online review compared to previous study that only covers food, service, ambience, and price. Food and service are the most influenced consumers' dining experiences, followed by ambience and price. The linkage between online review and rating are supported by [33]. Online reviews are also influenced by culture and ethnocentrism of certain countries. A study comparison between Chinese and American tourists found that Chinese visitors are less likely to give restaurants lower ratings and are more intrigued by the food on offer, whereas American visitors are more likely to be fun-seeking and less bothered by crowds.

G. *Comparison with Competitor Products*

Not many studies were conducted on product reviews. Majority studies have taken Amazon [49], [50], [69]–[72] or Rakuten Ichiba (Japan) marketplace [69] as their source of data. Rakuten Ichiba give more variety in sportswear and cloth products compared to Amazon [69]. Online reviews also could be used to compare with competitor products [72]. [71] demonstrates products positioning for profitable market segments can be analysed through online reviews while comparing with competitors. In his study, he showed the relationship through social network perspective. He reveals that the strength of ties has a beneficial impact on the review rating of a product, with weak ties having a greater impact than strong links. In addition, online review is useful when the title and content are similar [70].

Distinctively with other studies in product review, [73] explored emotion sentiment user's behaviour through online dating service (ODS) comments. In spite, the studies achieved a higher accuracy by combining lexicon-based methods and machine learning, category labels are manually annotated, which demands a lot of human labour which can used semi-supervised learning techniques to improve manual annotation in the future.

H. *Sentiment Analysis in Agriculture*

Most of the sentiment analysis in agriculture studies investigating the opinion of the price hike [74]–[76] and related to smart farming acceptance [77]–[81]. It is of vital importance to take into consideration the after-effect of the protests and riots by farmers, due to the economic problems, lack of subsidy and the spike in food and commodity prices [82]–[84]. These sentiments are often expressed by them on social media. It is also intriguing to investigate people's sentiments towards food industries [85]–[92].

Sentiment studies in agriculture were also conducted in supply chain management [93], [94], SMEs startup business [95], supply and demands [93], agriculture innovation research [96], agrobiodiversity index [97] and government policies in agriculture fields [98]–[100].

[101] and [102] has studied on agriculture products sentiment. In comparison to this study to be conduct, both [101] and [102] have analyse Chinese sentiment polarity. [101] focus on improvise BERT model while [102] compared accuracy between Bi-LSTM and BERT fine-tuning models, the Text-CNN.

In [101] study, he introduces the Focal Loss function, which instructs the model to concentrate on feature word samples with more ambiguous sentiment expression and agriculture typical sentiment, and reduces the weight of

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easy-to-classify samples in model training. In comparison to the baseline BERT model, the trained model outperformed it by 7.05 percentage points, reaching 89.86% on the test set. The result from [102] of comparison between Bi-LSTM and BERT fine-tuning models, the Text-CNN proves that the Text-CNN does exceptionally well at classifying sentiment in brief texts, such as agricultural Chinese comment data, performs roughly 4% better in comparison.

[101] highlights in the future works will test the model on different key domain other than agriculture in Chinese language. He also emphasizes to measure the compatibility model in processing multilingual datasets would be interesting. Although sentiment analysis is the most actively researched area; nonetheless, despite being such a potent instrument, it is not generally utilized in the agricultural sector.

In conclusion, online reviews have effects in consumer decision-making, use to increase brand strength and consumer loyalty, information dissemination, and generating buzz among prospective consumers. Evidently, literatures have shown that acceptance on Malaysia's agriculture products is still a gap in research. This study will focus on agriculture products produced by MSMEs Malaysia in Agrobazaar Mall in Shoppee and Lazada e-commerce. Table 1 summarizing reviews on the importance of sentiment mining.

TABLE I
THE IMPORTANCE OF SENTIMENT MINING

No	Sentiment Mining	
1.	Usefulness in Sales	[3], [45], [46], [47], [48], [49], [50]
2.	*Impact on Purchase Behavior*	[51]
3.	*Impact of Negative Comments*	[3], [53], [54]
4.	*Impact On Brand*	[55], [56], [57], [58], [59], [60], [61]
5.	*Consumer Satisfaction*	[15], [17], [30], [62]
6.	*Comparison with Competitor Products*	[50], [69], [49], [71], [72], [70]

VI. METHODOLOGY

This section exemplifies the method to extract sentiment and mine opinion from consumer reviews, using algorithm BERT transformer. BERT framework achieved breakthrough results in 11 natural language understanding tasks, including sentiment analysis, semantic role labelling, sentence categorization, and the disambiguation of polysemous words, or words with multiple meanings [103]. In 2018, Google introduced BERT and released it as open source [104], [105]. Pre-trained models (PTMs) are deep learning NLP models and neural networks architecture. It is a contextual word embedding that is words with same meaning have a similar representation. Pre-trained models are more popular than customed model because of their high accuracy, less time to train and easier implementation. BERT is pre-trained on a large corpus of unlabeled text, and then used to fined-tuned and transfer learning to specific task or domain of NLP. It is considered a reusable model which NLP developer doesn't have to build from scratch.

Firstly, problem identification is drawn up as the basis to develop a research methodology. Then, the underlining research objective and scope act as the guidelines in the accomplishment of a succinct research goal, and preventing the study from deviating.

Secondly, the data pre-processing phase is being conducted, in the acquisition of data. Data comments will be extracted from Agrobazaar's Mall in Shopee and eFamaPlace in Lazada e-commerce, using a web data scraper, and entered into an Excel spreadsheet. The reason Agrobazaar is choosen because it is the most widely centralized focused on agriculture SME's entreprenuers under FAMA [106]. Agrobazaar an e-commerce is an online agro-based products commerce under responsibility of Federal Agricultural Marketing Authority (FAMA) a statutory body under the Ministry of Agriculture and Food Security (MAFS) and is responsible to administrated, coordinating, regulating, and enhancing the marketing of agricultural products. One of the functions of FAMA is to market agro-food products from small and medium-sized enterprises (SMEs) through online e-commerce called Agrobazaar.

Thirdly, is the data processing phase, where the clean data is being processed to mine sentiment. The topics are categorized using the Modeling Latent Dirichlet Allocation (LDA) feature extraction method. Finally, a developed model will be derived from the analysed result, and will be visualized. The result will be validated against a confusion matrix, and triangulation to confirm the acceptance model will be done through an interview with related authorities.

An overview of the system, as shown in Fig. 2, followed by an in-depth task of the entire architecture in Fig. 3.

Fig. 5 An overview of the process

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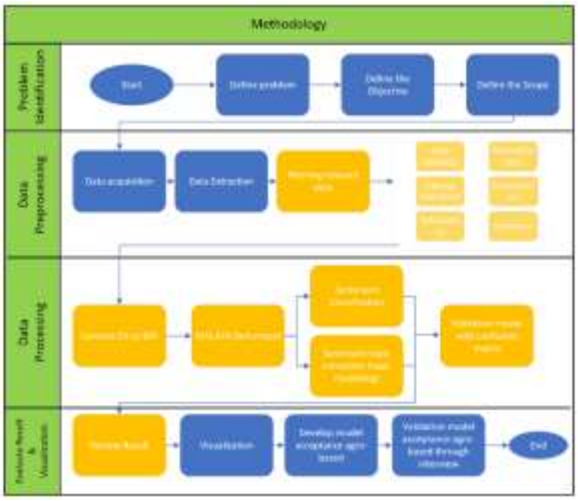

Fig. 6 An in-depth task of the entire architecture

VII. Conclusion

For a variety of reasons, studying and analysing feedback on Malaysian agricultural products via text mining internet reviews in the e-commerce sector is critical. Because of the growing importance of e-commerce, it is critical to understand client feedback in order to enhance product quality and match consumer expectations. Analysing online reviews gives useful insights that help firms and regulators find patterns, trends, and areas for development. Malaysia's agricultural sector can create a strong reputation, attract new consumers, and promote sustainable agriculture by actively listening to consumers, responding to negative feedback, and capitalising on favourable experiences. Text mining's scalability and efficiency enable real-time analysis of massive amounts of consumer feedback, providing stakeholders with data-driven insights for strategic decision-making. Finally, this study helps to the general development and competitiveness of the country. Despite the fact that this is a conceptual paper, it is envisaged that the work would help to enrich literatures for researchers' reference as well as have a substantial impact by providing stakeholders with data-driven insights for strategic decision-making upon fully completion of the research.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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