



Helpfulness Prediction Model for Thai IT Product Reviews

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Abstract. The rise of e-commerce platforms in Thailand has transformed shopping habits, where product reviews influence purchasing decisions. This research aims to propose a machine learning model that predicts the helpfulness scores of reviews, enabling efficient sorting and display to customers based on their levels of helpfulness, saving time and facilitating informed choices. In order to overcome the absence of a dataset for training the model, we implemented a dataset creation methodology specifically designed for reviews in Thai, addressing the lack of available data in Thai language. The pre-trained RoBERTa model is chosen based on its lowest MAE during cross-validation, demonstrating superior accuracy compared to alternative models, and its reliable performance on the test set validates its ability to make accurate predictions for unseen data. Furthermore, the implemented model significantly improves the review sorting order on an e-commerce platform, as indicated by participants who rated the implemented system higher in terms of perceived accuracy, requiring less user effort, and fostering greater user loyalty compared to the platform's baseline. These findings highlight the effectiveness of the implemented model in enhancing the user experience and assisting users in making informed decisions based on helpful reviews.

Keywords: Helpfulness prediction; Human annotate; Machine learning; Thai NLP.

1. Introduction

The rise of e-commerce platforms like Shopee and Lazada has completely transformed how people in Thailand shop, leading to significant growth in the online market. These platforms offer convenience and a wide range of products. A key feature is the ability to read product reviews, which greatly influence purchasing decisions. Thai consumers trust fellow customers' opinions when evaluating product quality, features, and satisfaction. Reviews build trust in online shopping, reducing the risks of buying unseen items. Market reports confirm the significant impact of reviews on consumer behavior. As the Thai e-commerce market grows, reliance on product reviews for informed decision-making will continue, allowing Thai shoppers to confidently enjoy online shopping's benefits.

Among all the groups of products sold on these platforms, IT gadgets are particularly popular and highly demanded in the marketing industry. However, these IT products can vary significantly in their usage characteristics, and they have specific quality indicators or descriptions that can pose a challenge for consumers. This variation makes it difficult for consumers to make informed purchase decisions based on the product descriptions provided.



As a result, consumers who read reviews may need to spend a lot of time reading a large number of reviews to find good ones that can help them make purchase decisions, especially for consumers who are not knowledgeable in the IT product group. In addition, they may also receive unreliable reviews, which further results in buyers losing confidence in purchasing those products.

One solution to tackle time-consuming review reading is to use machine learning to sort reviews based on their helpfulness score. By doing so, readers can save time by avoid wasting time on irrelevant or unhelpful ones. However, the lack of a well-defined training dataset poses a significant hurdle in this work. Existing studies have limited information on how they collected and labeled the data, making it difficult to generalize their findings. To address this issue, a complete training dataset specifically designed for Thai language and IT product reviews is necessary. This dataset would greatly assist in creating and assessing precise machine learning models, giving consumers more confidence when making purchasing choices.

In this study, a contribution will be made by developing a machine learning-based system to predict the helpfulness of product reviews in the Thai language. The aim is to utilize machine learning techniques to predict and sort reviews based on their helpfulness score. To achieve this, the need of having a dedicated training dataset for product reviews in the Thai language will be recognized. Therefore, another key contribution of this study will be the collection and creation of such a dataset comprising helpful product reviews in Thai.

2. Objectives

- To develop a machine learning model that effectively predicts helpfulness score of product reviews written in Thai for IT products on an E-commerce platform.
- To create a dataset of helpful product reviews in Thai Language for the IT product groups.

3. Literature Review

3.1 Helpfulness Prediction on Product Review

The prediction of the helpfulness of product reviews gained significant attention in the literature. Researchers have approached this task using supervised learning techniques, which involve training models on labeled data where the helpfulness of reviews is explicitly provided. They utilized various techniques to establish the correlation between review attributes and their level of helpfulness. For instance, [1] and [2] developed a predictive model using SVM. [3] and [4]. explored neural network algorithms for predicting product review helpfulness. [5] and [6] compare linear and non-linear models such as KNN, linear SVM, and neural network models such as DNN and CNN. [7] used BERT a pre-trained model to predict helpful review. they pinpoint difficulty of requiring handcrafted or specialized pre-processing. Regarding the lack of literature on predictive helpful review in the Thai language context. However, there have been papers explored Thai NLP. [8] conducted sentiment analysis on product reviews using four different models, including Linear model, LSTM, SVM, and SGD. [9] used decision tree to perform sentiment analysis on hotel reviews. [10] employed four classical models to classify five level of sentiment in social reviews.

The review of existing literature on predicting the helpfulness of product reviews highlights three major types of models: classical models, neural network algorithms, and pre-trained models. These three types of models should be considered for model selection in the study.

3.2 Dataset Creation Methodology for Helpfulness Prediction

Various studies have explored the creation of datasets for predicting the helpfulness of product reviews. Factors that influence review helpfulness include credibility, content, and expression [11]. Content factors, such readability, number of votes, and depth, including expertise, and

credibility, have also been identified in [12] and [13]. Additionally, factors such as product quality, sentiment, uncertainty, and product category have been considered in [14] and [15]. To determine the helpfulness, human annotation is commonly used to capture user opinions due to the subjectivity and individual perspectives of the product reviews [16]. This process can be challenging due to its time-consuming and resource-intensive nature. [17] and [18] propose efficient methods for annotating natural language processing (NLP) tasks by crowdsourcing with non-expert workers from platforms like Amazon Mechanical Turk. They demonstrate that using non-expert labels can be as effective as using annotations from experts. They also suggest using label scores instead of binary labels during training.

Currently, there is no study in create dataset in Thai for predict helpfulness in product review. To bridge this gaps, comprehensive and well-defined datasets are crucial. Our research aims to address these challenges by collecting and creating a dataset of helpful product reviews in the Thai language for IT products. This dataset will capture linguistic nuances and domain-specific characteristics, enabling accurate machine learning model to effectively predict and identify helpful Thai IT gadget review.

4. Methodology

4.1. Data Collection

The data collection methodology employed in this study utilized web scraping techniques to gather product reviews written in the Thai language from the renowned e-commerce platform, Shopee. The focus of the data collection was on five popular categories of IT products: smartwatches, keyboards and mice, speakers, earphones, and air purifiers. For each category, 240 reviews were collected, resulting in a total of 1,200 reviews. To ensure a fair representation of different opinions, 48 reviews were sampled from each set of 240 reviews, covering a range of ratings from 1 to 5 stars. This sampling strategy was designed to capture a diverse range of sentiments and viewpoints within the dataset. The scope of the data was explicitly limited to IT product reviews in the Thai language on Shopee. Data collection was specifically conducted from January 1, 2022, to April 30, 2023. The data scraped from each category was then filtered and pre-processed to collect the following fields: Review Time, Star Rating, and Review Text. These features are depicted in Figure 1.

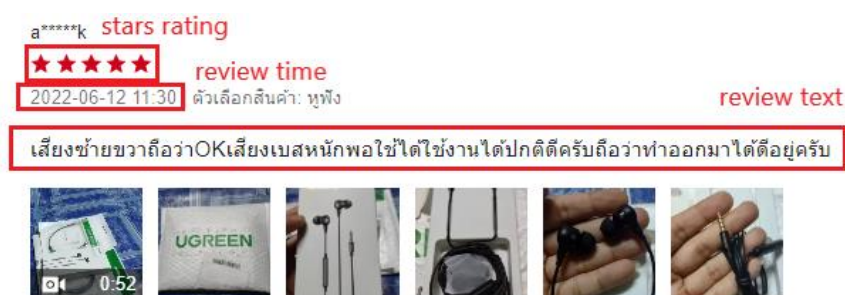


Figure 1. Data Collection from Shopee

4.2. Data Labeling

Data labeling methodology refers to the process of assigning meaningful tags or annotations to raw data. This crucial step involves human annotators who meticulously review and interpret the data, ensuring accurate labeling. In our study, we followed the methodology outlined by [11]. Each review was assessed based on three primary criteria: credibility, content, and expression. The credibility criterion focused on evaluating the trustworthiness, uncertainty, and reliability of the reviews. The content criterion aimed to assess the richness and depth of information provided in the reviews. Lastly, the expression criterion focused on assessing the



mood and writing style of the reviewers. These criteria encompassed various aspects, including user sentiment, behavioral patterns, consistency. By considering these factors, we aimed to ensure a thorough analysis of the reviews.

Our annotation methodology involved a scoring system based on a scale of 0 to 3 for each criterion. Each annotator assessed the credibility, content, and expression of the reviews and assigned a score reflecting the extent to which the criteria were met. A score of 0 indicated that the criterion was not evident or poorly represented in the review, while a score of 3 indicated a clear and substantial representation of the criterion. To determine the overall helpfulness of each review, we summed the scores assigned to credibility, content, and expression. This summation score ranged from 0 to 9, representing the overall perceived helpfulness of the review. This helpfulness score served as the target variable for the helpfulness prediction task, which aimed to predict the level of helpfulness based on the annotated criteria.

4.3. Data Preprocessing

This section aims to provide the steps taken to clean and prepare the data for predicting the helpfulness of Thai reviews in the study. Data preprocessing is considered essential for enhancing the accuracy of the predictive model and addressing the challenges posed by the unique characteristics of the Thai language. The absence of word spaces and full stops, slang, multilingual language, including English words, and the presence of numbers and emoticons in reviews, making it difficult for machine learning models to accurately analyze the text. The data preprocessing techniques outlined in the paper [19] were followed to tackle these issues. The preprocessing steps involved symbol removal, number removal, English word removal, emoji and emoticon removal, text normalization, word tokenization, whitespace and tab removal, and single character removal.

4.4 Modeling

In this section, predictive models were developed to determine the helpfulness score of IT *product or gadget* reviews based on their informative content. Supervised learning techniques, specifically regression, were utilized to train and evaluate the models, establishing a relationship between the informative content of the reviews and their corresponding helpfulness scores. To compare different modeling approaches, three types of machine learning models were considered: classical models, neural network models, and pre-trained models. The inclusion of these three model types was informed by existing literature papers [5], [6], and [7] that have employed these model types to predict review helpfulness.

4.4.1 Classical Models

We used four classical models, including Linear Regression model [20], Support Vector Machine model [21], Decision Tree model [22], and K Nearest Neighbors model [23]. These models were trained on regression approach, analyze the informative content of the review using methods convert the text into numerical features, establish pattern and relationship between the text features and the helpfulness score, allowing explore different approaches in predicting helpfulness based on informative content from reviews.

4.4.2 Neural Network Models:

We used four neural network architectures, including Deep Neural Networks (DNN) [24], Recurrent Neural Networks (RNN) [25], Convolutional Neural Networks (CNN) [26], and Long Short-term Memory (LSTM) [27]. All of these models were trained using regression approach. They can learn complex relationships and abstract representations from the text data. In this case, the neural network would typically consist of an embedding layer, which converts the text into a dense vector representation, The network learns the relationship between the review



text and the helpfulness score by adjusting the weights during the training process. Enabling them to make predictions based on the learned representations.

4.4.3 Pre-trained Models

We utilized four pre-trained models: WangchanBERTa [28], BERT [29], RoBERTa [30], and Thai-NER [31]. These models were developed by researchers in the field of natural language processing and initially trained by on a large-scale corpus of Thai language and, which included various textual sources such as social media posts, online reviews, news articles. The main objective of pre-training models was to capture language understanding for challenging aspects specific to the Thai language, including grammar, patterns, semantics, and contextual comprehension. To adapt these pre-trained models for our review helpfulness prediction task, we employed a process known as transfer learning. This involved fine-tuning the models using our labeled dataset, which consisted of review texts and their corresponding helpfulness scores. The fine-tuning process adjusted the internal weights and biases of the models to minimize the difference between the predicted helpfulness scores and the actual scores, enabling the models to make predictions of helpfulness scores.

4.5 Evaluation

This section presents methods to evaluate the performance of our system, including model performance evaluation and an assessment based on user experience.

4.5.1 Model Performance Evaluation

Model performance evaluation was conducted on the models with the aim to select the best model for our system by measuring the accuracy in predicting the helpful score of a review. The mean absolute error (MAE) was calculated to determine the average difference between the estimated score and the actual score of the review. This approach, presented by [14] indicates that a lower MAE indicates better alignment between the model's predictions and the actual helpfulness score. Furthermore, other metrics such as training time and testing time were also considered to support the process of model selection.

4.5.2 User Experience Evaluation

A user experience evaluation was conducted to assess the sorting of reviews based on their helpfulness, with the goal of measuring user experiences and satisfaction. The evaluation method included a comparison between the original review sorting method from the e-commerce platform and the implemented model for predicting helpfulness. Three criteria were included as user evaluation measures [32]: perceived accuracy, user effort, and user loyalty. Participants were asked to respond to three key questions:

- On a scale of 1 to 5 (1 = Not confident at all, 5 = Very confident), how confident are you in the accuracy of the product review sorting order in presenting the most valuable reviews?
- On a scale of 1 to 5 (1 = Made it much harder, 5 = Made it much easier), did the product review sorting order make it easier for you to locate the most relevant and informative reviews without much effort?
- On a scale of 1 to 5 (1 = Very dissatisfied, 5 = Very satisfied), how satisfied are you with the product review sorting order in helping you make informed decisions?

The intent behind the first question is to evaluate the perceived accuracy and assess how users perceive the reviews as tailored to their informative content, making it easier for them to identify helpful reviews. The second question aims to measure the subjective effort or time

spent by users in completing the review sorting and decision-making process, and the final question measures user loyalty, indicating overall user satisfaction.

5. Result and Discussion

5.1. Model Selection

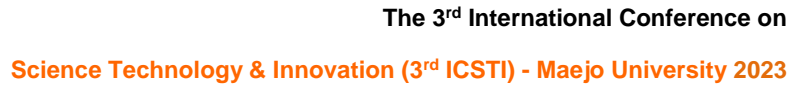
This section explains how we choose the most appropriate machine learning model for helpfulness prediction. The primary criterion assessed is the Mean Absolute Error (MAE). Train time refers to the time required, in seconds, to fully train the model until it reaches a satisfactory or optimal performance level. Test time is the duration, measured in seconds, it takes for the model to process and make predictions for each individual review in the testing data. The result of each model obtained by performing cross-validation are shown in Table 1.

Table 1 Model Performance Evaluation from Training

No.	Model	MAE	Train time (s)	Test time (s)
Classical Models				
1	Linear Regression	1.8838	0.46	0.000004
2	Support Vector Machine	1.0587	8.49	0.000152
3	Decision Tree	1.3793	1.95	0.000003
4	K-Nearest Neighbors	1.3119	1.67	0.000194
Neural Network Models				
5	Deep Neural Network	1.6060	25.31	0.000062
6	Recurrent Neural Networks	1.6508	35.29	0.000121
7	Convolutional Neural Networks	1.1905	12.27	0.000068
8	Long Short-term Memory	1.6131	73.60	0.000656
Pre-train Models				
9	WangchanBERTa	1.1974	2361.29	0.428230
10	BERT	1.2627	2048.74	0.265723
11	RoBERTa	1.0223	2483.60	0.338920
12	Thai-NER	1.1939	2680.10	0.297517

Among these models, the pre-trained model RoBERTa exhibited the lowest MAE of 1.0223, indicating higher accuracy in predicting helpfulness score of the IT gadget review among all other models. Therefore, based on its superior performance in terms of MAE, the pre-trained model RoBERTa was chosen as the review sorting model for the task in this study. Considering that the training process is performed only once and the focus is on selecting the most accurate model, the slightly longer training time of the RoBERTa model becomes less significant. Additionally, after selecting the pre-trained model RoBERTa based on its superior performance in terms of MAE during cross-validation, we further evaluated its performance on a test set. The MAE obtained on the test set was 1.0447, which is very close to the MAE from the validation set (1.0223). This result demonstrates the generalization ability of RoBERTa to accurately predict the helpfulness score of unseen data. Therefore, we can confidently proceed with utilizing RoBERTa as the chosen model for predicting the helpfulness score of IT gadget reviews, as it consistently on both validation and test data.

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5.2 User Experience Evaluation

This section explains the user experience evaluation results conducted for the study. A new ~~validation~~ dataset was gathered, consisting of 30 reviews for each category of the same product, resulting in a total of 150 reviews. Both the baseline and the model utilized the same validation set. A total of 30 participants took part in the user study to evaluate two versions of the review order. Each participant received two sets of materials: the original review order from Shopee (the baseline) and the review order based on our model, sorted from high helpfulness to low helpfulness scores. Participants rated their satisfaction on a scale from 1 to 5 for the criteria mentioned in 4.5.2 The results of the user study are shown in Figure 2.

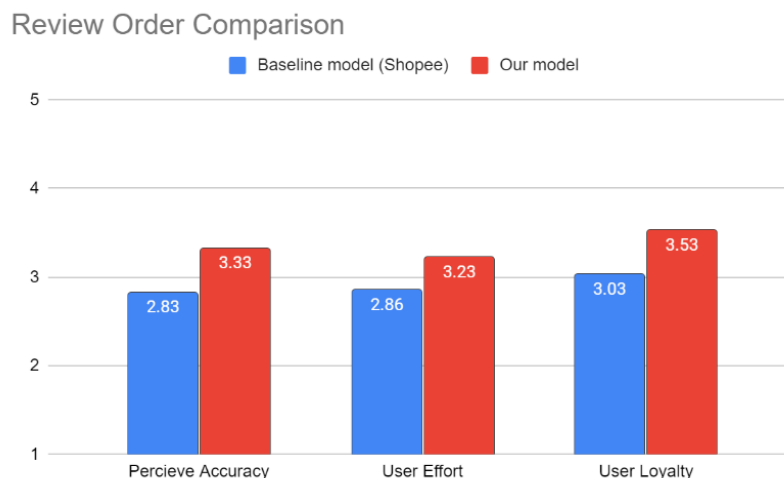


Figure 2 Comparing Satisfaction Scores of Review Order

According to the participant ratings, The reviews sorted by our implemented model have been perceived to exhibit several improvements compared to the baseline. Our model demonstrates higher accuracy in presenting reviews, as it received a rating of 3.33, surpassing the baseline model's rating of 2.83. Additionally, our model requires less user effort, as indicated by its rating of 3.23, outperforming the baseline rating of 2.86. Furthermore, our model fosters higher user loyalty, receiving a rating of 3.53, while the baseline obtained a rating of 3.03. These ratings highlight the enhanced performance and user experience provided by our model in terms of accuracy, user effort, and user loyalty, indicating its effectiveness in improving the review order on Shopee.

6. Conclusion

This research aims to develop a machine learning system that predicts the helpfulness of product reviews in the Thai language for IT products. This will address the challenge of time-consuming review reading and provide consumers with a more efficient way to finding reliable and informative product reviews for informed purchasing decisions. We have defined two objectives for this study. First, we create a dataset of product reviews in Thai, specifically on IT product reviews. Second, we utilize machine learning techniques and develop a system that accurately predicts and sorts reviews based on their helpfulness score. The methodology involved data collection through web scraping of Thai product reviews from Shopee. Data labeling was conducted by assessing credibility, content, and expression criteria, assigning scores to determine the overall helpfulness of each review. Data preprocessing techniques were applied to address challenges posed by the Thai Natural Language Processing. Three types of models: classical, neural network, and pre-trained models were developed and



compared to predict the helpfulness scores of reviews based on informative content. The performance was evaluated using the mean absolute error (MAE) metric. User experience evaluation compared the implemented model with Shopee's original review sorting, assessing perceived accuracy, user effort, and loyalty. Participants rated confidence, ease of locating relevant reviews, and satisfaction with the sorting order's assistance in decision-making. The results of our study demonstrate that the pre-trained model RoBERTa is a chosen model for predicting the helpfulness score of IT gadget reviews. It exhibited the lowest MAE during cross-validation, indicating superior accuracy compared to other models. Additionally, the generalization ability of RoBERTa was confirmed by its similar performance on the test set. This model selection process ensures reliable predictions for unseen data. Furthermore, the user experience evaluation revealed that the implemented model significantly improved the review sorting order on Shopee. Participants rated our system higher in terms of perceived accuracy, requiring less user effort, and fostering greater user loyalty compared to the Shopee baseline. These findings highlight the effectiveness of the implemented model in enhancing the user experience and assisting users in making informed decisions based on helpful reviews.

For future work, the scope of this research can be expanded to include other categories of products, allowing for the development of a multilingual system capable of handling diverse types of reviews. To enhance the accuracy and performance of the system, different model approaches, such as transformer-based models or ensemble techniques, can be explored. Furthermore, investigating the incorporation of user feedback and preferences into the model to personalize the review sorting process would be valuable.

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References

- [1] Zhang, Y., Zhang, D. 2014 Automatically predicting the helpfulness of online reviews. In Information Reuse and Integration (IRI), 2014 IEEE 15th International Conference on, IEEE.
- [2] Ngo-Ye, T. L., Sinha, A. P. 2014 The influence of reviewer engagement characteristics on online review helpfulness: A text regression model. Decision Support Systems, Vol. 61, pp. 47-58.
- [3] Goswami, K., Park, Y., Song, C. 2017 Impact of reviewer social interaction on online consumer review fraud detection. Journal of Big Data, Vol. 4, No. 1, pp. 15.
- [4] Olatunji, I. E., Li, X., & Lam, W. 2019 Context-aware helpfulness prediction for online product reviews. In Asia information retrieval symposium, Springer, pp. 56-65.
- [5] Kong, L., Li, C., Ge, J., Ng, V., & Luo, B. 2020 Predicting product review helpfulness: a hybrid method. IEEE Transactions on Services Computing.
- [6] Sharma, S. P., Singh, L., & Tiwari, R. 2023 Prediction of Customer Review's Helpfulness Based on Feature Engineering Driven Deep Learning Model. International Journal of Software Innovation, Vol.11, No.1
- [7] Bilal, M., & Almazroi, A. A. 2022 Effectiveness of Fine-tuned BERT Model in Classification of Helpful and Unhelpful Online Customer Reviews. Electronic Commerce Research.
- [8] Bowornlertsutee, P., Paireekreng, W. 2022 Emotion-based sentiment analysis model for categorizing online product review. Journal of Engineering and Digital Technology (JEDT), Vol. 10, No. 1.



- [9] Manhem, M., Dolah, S., Chunkaew, S., Mak-on, S. 2020 Model for the Classification of Feelings of Reviews Using Techniques Decision Trees: Case Studies Hotel Reservation Web Site. Journal of Science and Technology, Songkhla Rajabhat University, Vol. 2, No. 2.
- [10] Thetmueang, R., Jirawichitchai, N. 2017 Thai Sentiment Analysis of Product Review Online Using Support Vector Machine. Engineering Journal of Siam University, Vol. 18, No. 34.
- [11] Li, M., Huang, L., Tan, C.-H., Wei 2013 Helpfulness of online product reviews as seen by consumers: source and content features. International Journal of Electronic Commerce, Vol. 17, No. 4, pp. 101-136.
- [12] Almutairi, Y. A., Abdullah, M., Alahmadi, D. 2019 Review Helpfulness Prediction: Survey Periodicals of Engineering and Natural Sciences ISSN 2303-4521, Vol. 7, No. 1, June, pp. 420-432.
- [13] Wu, J. 2017 Review popularity and review helpfulness: A model for user review effectiveness. Decision Support Systems, Vol. 97, No. 6, pp. 92-103.
- [14] Siering, M., Muntermann, J. 2013 What Drives the Helpfulness of Online Product Reviews? From Stars to Facts and Emotions. In Proceedings of the 11th International Conference on Wirtschaftsinformatik, Leipzig, Germany.
- [15] Barbosa, J. L., Moura, R. S., Santos, R. L. d. S. 2016 Predicting Portuguese Steam Review Helpfulness Using Artificial Neural Networks. In Proceedings of the 22nd Brazilian Symposium on Multimedia and the Web, ACM.
- [16] Singh, J. P., Irani, S., Rana, N. P., et al. 2017 Predicting the 'helpfulness' of online consumer reviews. Journal of Business Research, Vol. 70, No. 6, pp. 346-355.
- [17] Snow, R., O'Connor, B., Jurafsky, D., Ng, A. Y. 2008 Cheap and Fast — But is it Good? Evaluating Non-Expert Annotations for Natural Language Tasks. Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, pp. 254-263, Honolulu.
- [18] Passonneau, R. J., Carpenter, B. 2014 The Benefits of a Model of Annotation. Transactions of the Association for Computational Linguistics, Vol. 2, pp. 311-326.
- [19] Khamphakdee, N., & Seresangtakul, P. 2021 Sentiment Analysis for Thai Language in Hotel Domain Using Machine Learning Algorithms. Acta Informatica Pragensia, Vol. 10, No. 2, pp. 155-171.
- [20] Galton, F. 1886 Regression Towards Mediocrity in Hereditary Stature. The Journal of the Anthropological Institute of Great Britain and Ireland, Vol. 15, pp. 246-263.
- [21] Cortes, C., & Vapnik, V. 1995 Support-vector networks. Machine Learning, Vol. 20, No. 3, pp. 273-297.
- [22] Quinlan, J. R. 1986 Induction of decision trees. Machine Learning, Vol. 1, No. 1, pp. 81-106.
- [23] Cover, T., & Hart, P. 1967 Nearest neighbor pattern classification. IEEE Transactions on Information Theory, Vol. 13, No. 1, pp. 21-27.
- [24] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. 1986 Learning representations by back-propagating errors. Nature, Vol. 323, No. 6088, pp. 533-536.
- [25] Elman, J. L. 1990 Finding structure in time. Cognitive science, Vol. 14, No. 2, pp. 179-211.
- [26] Hochreiter, S., & Schmidhuber, J. 1997 Long short-term memory. Neural computation, Vol. 9, No. 8, pp. 1735-1780.
- [27] Fukushima, K. 1980 Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biological cybernetics, Vol. 36, No. 4, pp. 193-202.
- [28] Lowphansirikul, L., et al. 2021 WANGCHANBERTa: Pretraining Transformer-Based Thai Language Models. arXiv preprint arXiv:2101.09635v2.



- [29] Devlin, J., et al. 2018 BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Vol. 1, pp. 4171-4186.
- [30] Liu, Y., et al. 2019 RoBERTa: A robustly optimized BERT pretraining approach. arXiv preprint arXiv:1907.11692.
- [31] Suriyachay, K., et al. 2021 Enhancement of Character-Level Representation in Bi-LSTM model for Thai NER. Science & Technology Asia, Vol. 26, No. 2, pp. 61-78.
- [32] Hu, R., Pu, P. 2009 A comparative user study on rating vs. personality quiz-based preference elicitation methods. Proceedings of the 2009 International Conference on Intelligent User Interfaces, Sanibel Island, Florida, USA, pp. 293-296.