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Hybrid WangchanBERTa Architectures for Multi-Class Thai Sentiment Analysis

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ABSTRACT

The rapid growth of the restaurant industry in Thailand has intensified the importance of online reviews, which significantly shape customer perceptions and influence business performance. Sentiment analysis has emerged as an effective computational approach for extracting customer opinions from such reviews; however, multi-class sentiment classification in Thai remains challenging due to the language's non-segmented structure and the issue of class imbalance. This study investigates three hybrid deep learning models—WangchanBERTa-MLP, WangchanBERTa-CNN, and WangchanBERTa-BiLSTM—by integrating WangchanBERTa, a Thai-specific pre-trained language model, with different neural architectures. Using a balanced dataset of restaurant reviews obtained through SMOTE, the models were evaluated based on accuracy, precision, recall, and F1-score. The experimental results show that WangchanBERTa-BiLSTM performed the best overall, achieving an accuracy of 85.22% and significantly improving the classification of neutral and positive sentiments compared to the BERT-based models and other hybrid methods.

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1. INTRODUCTION

The number of restaurants in Thailand has grown very quickly in recent years, with steady growth in the food service sector. Online reviews these days are very important in shaping consumer sentiment and have a direct impact on restaurants' reputations and bottom lines. Thai food, renowned for its depth of flavour and culture, tends to generate extensive online discussion, as customers complain and share opinions across the web. To better understand what customers are looking for, sentiment analysis of these reviews is critical. Labelling sentiment by hand is time-consuming and likely to be inaccurate. To address the problem, sentiment analysis has become a computational method for automatically assigning emotional polarity to text.

Classic machine learning methods such as KNN (K-Nearest Neighbours), logistic regression, SVM (Support Vector Machines), and Naïve Bayes were successfully employed for restaurant review sentiment classification [1-6]. For example, Hamad *et al.* [2] studied the customer views on restaurants on Twitter since it is not possible to process the huge amount of information manually. The authors employed the Naïve Bayes algorithm to label the tweets as either positive or negative views. Based on actual Twitter data, the system posted performance measures of 68% precision, 80.07% recall, 73% accuracy. Obiedat *et al.* [4] suggested a combined sentiment analysis methodology with SVM and PSO (Particle Swarm Optimization), along with some oversampling techniques for handling imbalance in the dataset. Based on reviews gathered from Jeeran, an Arabic social platform, the system adapted feature weights and conducted dataset balancing using methods including SMOTE, ADASYN, and SVM-SMOTE. Experimental results indicate the supremacy of the PSO-SVM methodology over other classification algorithms with better accuracy, F1-score, G-mean, and AUC.

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Deep learning has more recently been the favourite with its capability to automatically learn complex representations from raw text with scalable and extremely accurate solutions. Deep learning has been applied in some studies to restaurant review sentiment analysis. For example, Hossain *et al.* [7] integrated CNN (Convolutional Neural Networks) and LSTM (Long Short-Term Memory) to categorize restaurant reviews in Bangladesh and achieved 94.22% accuracy. Aswin *et al.* [8] used a cyberbullying detection in Indonesian social media based on three pre-trained BERT (Bidirectional Encoder Representations from Transformers) models. Among these three, IndoBERT performed the best with a mean F1-score of 82%. Chaudhari *et al.* [9] have also employed BiLSTM (Bidirectional LSTM) and BiGRU (Bidirectional Gated Recurrent Units) for classifying Bangalore restaurant reviews on Zomato. They also employed Word2Vec, VADER, and sentiment intensity analysis. The accuracy was 98.6%. Mutinda *et al.* [10] proposed LeBERT, which combined sentiment lexicons, n-grams, BERT, and CNN to perform binary sentiment analysis with an F1-score of 88.73%. Similarly, Sarsabene *et al.* [11] proposed a hybrid of CNN and Bi-RNN and SVM model for aspect-based sentiment analysis of French smartphone and restaurant reviews with an F1-score of 94.05%. Songram *et al.* [12] compared machine learning and deep learning models with various feature representations for sentiment analysis of Thai restaurant reviews. Reviews were pre-processed and vectorized via Boolean, TF, and TF-IDF weighting and then classified. SVM with TF-IDF produced the best results with excellent F1-scores for positive and negative classes.

From previous papers, BERT has always demonstrated high accuracy and efficiency in sentiment analysis tasks [13]. Its biggest asset is its ability to capture contextual information at the sentence level; it is best suited for sentiment analysis of restaurant reviews, which tend to be extremely context dependent. Therefore, BERT has been widely applied for sentiment analysis across multiple languages, including Thai. For example, Ritthisit *et al.* [14] compared three Thai BERT models, multilingual BERT, BERT-base-thai, and WangchanBERTa, for multiclass sentiment classification of restaurant reviews. WangchanBERTa achieved the highest accuracy at 83.72%. Although BERT is highly effective, it still struggles to clearly differentiate between positive and neutral sentiments for multi-class sentiment classification of Thai restaurant reviews [14]. In this paper, the hybrid deep learning models based on a Thai-adapted RoBERTa model, WangchanBERTa, are studied to improve performance for multi-class sentiment classification of Thai restaurant reviews. The contributions of the research are: (1) unlike prior studies that relied on BERT or deep learning, this work leverages a Thai-specific pretrained model, WangchanBERTa, integrated with CNN, BiLSTM, and MLP architectures for a comparative evaluation, and (2) exploration of hyperparameter tuning, particularly the number of training epochs, to identify the optimal setting for high-quality prediction.

The remainder of this paper is organized as follows: Section 2 presents an overview of all models used in the hybrid framework, as well as the models used for comparison, including multilingual BERT models, WangchanBERTa, CNN, BiLSTM, and MLP. Section 3 gives the details of the proposed models. Sections 4 and 5 present the experimental results and discussion, and Section 6 concludes with future directions for research.

2. THE BACKGROUND ALGORITHMS

2.1 BERT

Transformer architectures [15] have emerged as a baseline model for today's NLP (Natural Language Processing) applications. The self-attention mechanism in the Transformer allows the architecture to effectively capture long dependencies in the data, thereby achieving state-of-the-art results in many languages, including low-resource languages like Thai. BERT [16] stands for Bidirectional Encoder Representations from Transformers. It was trained using an MLM (Masked Language Model) task and an NSP (Next Sentence Prediction) task and led to significant improvements in many NLP tasks. BERT learns the contextual meaning of a word from both its left and right surroundings. This bidirectionality also makes it extremely helpful for sentiment analysis, where subtle context must be captured (e.g., sarcasm or negation). For input representation, each input sentence is converted into tokens and represented as embeddings shown in (1), where E_{token} represents the word-piece embeddings corresponding to the tokens, $E_{segment}$ represents embeddings that indicate sentence A or sentence B (used in next sentence prediction), and $E_{position}$ represents positional embeddings to represent the token's position in the sequence. BERT uses a stack of 12 transformer encoder layers, each with multi-head self-attention and feed-forward networks. For each layer, the self-attention mechanism is shown in (2), where $Q = XW^Q$ is the query matrix, $K = XW^K$ is the key matrix, $V = XW^V$ is the value matrix, d_k is the dimension of the key vectors, and X is the input embeddings. This allows each token to attend to all other tokens in the sentence. After attention, each token embedding is passed through a position-wise feed-forward network. The feed-forward layer is shown in (3), where W_1, W_2, b_1, and b_2 are learned weights and biases, and x is the output from the attention layer. For sentiment analysis (e.g., positive, negative, neutral), the output layer is shown as (4), where H_{CLS} is the final hidden state of the [CLS] token from BERT, and W_c, b_c are classification layer weights and bias terms.

$$E = E_{token} + E_{segment} + E_{position} \tag{1}$$

$$self-Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

$$FFN(x) = \mathrm{GELU}(xW_1 + b_1)W_2 + b_2 \tag{3}$$

$$y = soft\max(H_{CLS}W_c + b_c) \tag{4}$$

After the success of BERT, there have been many variations of BERT-based models developed. These variations help increase the diversity and strength of the BERT family models. For example, mBERT (Multilingual BERT) [17] was developed based on the BERT model. It was pre-trained using data from the Wikipedia pages of 104 languages, including Thai. In mBERT, there is a unified WordPiece vocabulary. mBERT was trained in all languages simultaneously, which helps the model learn cross-lingual representations without having to align the data and without the need for data alignment or parallel text. mBERT was developed using the BERT-Base framework. It has 12 layers, 768-dimensional vectors, and 12 heads. It was trained using the MLM and NSP. Using combined sub-word units and parameters, mBERT can learn representations across different languages. These languages can vary from low-resource languages to high-resource languages.

RoBERTa (Robustly Optimized BERT Pre-training Approach) [18] was developed as an optimized variant of BERT with optimized training settings. In the model, the task of predicting the next sentence is eliminated, and larger batch sizes, larger amounts of data, and dynamic masking are applied. These modifications significantly improve the model's performance. RoBERTa follows the BERT architecture, with 12 layers, 768 hidden units, and 12 self-attention heads in the base variant. Although structurally based upon BERT, there are some fundamental changes in the RoBERTa pre-training process to make the model's performance robust and optimal. These modifications include the removal of the NSP task, replacing the static masking process, and using larger corpora with longer sequences and larger batch sizes.

ALBERT [19] can be considered a lightweight variant of the BERT model that was developed to reduce the number of parameters without compromising performance. It consists of two key changes. First, ALBERT factorized embedding parameterization, in which the number of vocabulary embeddings and hidden layer units are treated as independent factors rather than multiplying one by the other, reducing unnecessary parameters. The second change is cross-layer parameter sharing, where weights in all transformer layers are shared to reduce redundancies and memory inefficiencies. Also, ALBERT replaces the NSP task in BERT with SOP (Sentence Order Prediction) in order to increase the model‘s understanding of discourse and to make it much more focused on coherence, where tasks involve correctly identifying the order between two sentences instead of simply predicting whether sentences are consecutive. Experiments conducted using standard benchmarks such as GLUE and SQuAD demonstrated the effectiveness of ALBERT in achieving state-of-the-art performance using far fewer parameters than in BERT.

XLM-RoBERTa [20] is an advanced multilingual transformer model developed as an extension of RoBERTa, particularly designed to handle large-scale cross-lingual understanding tasks. It takes advantage of larger-scale multilingual datasets by using the MLM task alone without NSP in order to enhance the effectiveness of contextual understanding. XLM-RoBERTa was trained on 100 languages using the CommonCrawl dataset and SentencePiece tokenization to ensure greater linguistic diversity and enable the model to learn complex syntactic and semantic relationships from linguistically diverse languages. It uses a robust optimization strategy, including dynamic masking and large-batch training, which enhances generalization in both high-resource and low-resource settings. Empirical evaluations demonstrate that XLM-RoBERTa consistently outperforms mBERT and XLM across a wide range of cross-lingual benchmarks.

ELECTRA (Efficiently Learning an Encoder that Classifies Token Replacements Accurately) [21] is a transformer-based pre-trained model that seeks to enhance efficiency as well as performance beyond other traditional masked language models like BERT. In addition to using the task of predicting masked tokens, ELECTRA proposes the use of RTD (Replaced Token Detection), where a small-scale generator replaces tokens in the input, and a discriminator predicts whether tokens have been replaced. Although ELECTRA was pre-trained on large English corpora, its performance has been evaluated on a wide range of NLP tasks. These include downstream benchmarks such as GLUE, as well as question-answering datasets like SQuAD 1.1 and SQuAD 2.0. In addition, ELECTRA has also been applied to token-level tasks, including chunking. It can thus be gathered from the performance analysis that ELECTRA outperforms or equals other closely related architectures like BERT and RoBERTa on these downstream tasks. The performance of ELECTRA has therefore led to widespread adoption in NLP tasks in English and multilingual settings.

In the case of Thai NLP, the most popular and widely used model adaptation is WangchanBERTa [22]. WangchanBERTa is based on the RoBERTa

Table 1: *Comparative summary of extended BERT-based models.*

Model	Core Methodology	Dataset for training	Language	Results
mBERT	Joint multilingual training with shared WordPiece vocabulary enabling cross-lingual transfer	Multilingual Wikipedia	104 languages (including Thai)	Strong cross-lingual generalization without parallel corpora
RoBERTa	Removes NSP; dynamic masking; larger batch sizes; longer training	160 GB corpus (BookCorpus, CC-News, OpenWebText, Stories)	English	~88 GLUE benchmark score
ALBERT	Parameter-efficient architecture with factorized embedding parameterization and cross-layer parameter sharing; SOP objective	BooksCorpus , and English Wikipedia	English-only in its original version. Multilingual adaptations exist (mALBERT)	~89 GLUE score ~92 F1-score on SQuAD 2.0
XLM-RoBERTa	Multilingual extension of RoBERTa trained with cross-lingual objectives	2.5 TB filtered CommonCrawl	100 languages (including Thai)	~97 accuracy on XNLI ~76.7 F1 on MLQA
ELECTRA	Replaced Token Detection (RTD) pre-training for sample-efficient learning	English Wikipedia and BooksCorpus	-English-only in the original version. -Multilingual adaptations exist (mELECTRA), not including Thai	~85 GLUE score
Wangchan BERTa	Thai-specific RoBERTa-based model trained on large Thai corpora	large-scale Thai corpus	Thai	~78- 96 F1-score

model, which is an improvement upon the standard BERT model in that it uses dynamic masking, NSP, and utilizes larger datasets with longer sequences and larger batch sizes. These modifications to the model are especially useful in handling Thai since it has no explicit word boundaries and is highly lexically ambiguous. One of the main influential factors in the effectiveness of WangchanBERTa is its training corpus, being the aggregation of multi-billion-scale Thai corpora from a wide variety of digital sources such as social network interactions, news, the web, and Wikipedia. The large dataset enables the model to learn colloquial expressions, formal speech, compound words, and terms of art found in greater numerosity in Thai speech. WangchanBERTa uses SentencePiece, an optimized tokenizer suitable for Thai scripts, to process large flows of text without spaces, achieving greater linguistic cohesion at the sub-word level than in multilingual models. WangchanBERTa demonstrates the effectiveness of exploiting architectural optimization based on languages in terms of large-scale monolingual pre-training data in boosting NLP tasks in non-segmented languages with complex morphology like Thai. The success of WangchanBERTa shows the virtue of having locality-based transformer models in understanding languages and cultures, especially languages like Thai that are underrepresented in multilingual models.

Based on prior studies utilizing BERT, it is evident that numerous variants such as mBERT, RoBERTa, ALBERT, XLM-RoBERTa, ELECTRA, and WangchanBERTa have been developed to enhance performance and reduce computational costs in various ways. To summarize the models, a comparative overview is presented in Table 1.

Although a wide range of models has been developed within the BERT family, prior research consistently shows that multilingual models typically underperform when compared with monolingual models that are fine-tuned for a specific high-resource language [23-26]. In the context of Thai language processing, WangchanBERTa is a monolingual model for Thai that achieves high accuracy across many tasks. Consequently, this study adopts WangchanBERTa as the primary baseline model. Nevertheless, multilingual models that support Thai remain of interest, and thus, this work also evaluates selected multilingual transformer models for the task of multi-class Thai sentiment analysis to assess their comparative effectiveness.

2.2 Deep Learning Models

Several works have focused on hybrid architectures that integrate BERT with other components of deep learning in order to produce superior performance in sentiment analysis tasks. For example, Rahman *et al.* [27] presented a hybrid model comprising BERT and BiLSTM in order to exploit the benefits of both in extracting contextual representations. The model was able to produce better performance than RoBERTa-base, RoBERTa-GRU, and RoBERTa-LSTM in standard sentiment analysis tasks with an accuracy and F1-score of 85.12% and 85.11%, respectively. Similarly, Jahin *et al.* [28] introduced TRABSA, a hybrid architecture combining RoBERTa, BiLSTM, and an attention layer. Their model, trained on a large multilingual tweet dataset, reached 94% accuracy. Moreover, other popular hybrid models incorporated BERT in contextual embeddings and CNN in feature extraction. Kumar *et al.* [29] applied an ensemble of both BERT and CNN in COVID-19 datasets and demonstrated how the combined model resulted in more accurate sentiment classification through the utilization of BERT's deep context and CNN capabilities in pattern detection. BERT and CNN showed an accuracy of 89%. Murfi *et al.* [30] discovered that the addition of BERT's contextual features to CNN-RNN resulted in a remarkable increase in the accuracy of Indonesian sentiment analysis tasks beyond the capability of conventional embeddings. Mutinda *et al.* [10] enhanced the baseline representation by developing LeBERT (Lexicon-Enhanced BERT) embeddings, which can then be classified using CNN, thereby proving that such a combination methodology, blending knowledge of lexicons with the deeper understanding of context, can achieve 82.52% accuracy. Also, simple models, such as the MLP (Multi-Layer Perceptron) model, were combined with BERT as the custom classifier. For instance, Chowdhury *et al.* [31] proposed a hybrid approach using fine-tuned SBERT embeddings with the custom MLP classifier in sentiment analysis tasks in Tamil and Tulu languages, which suffer from data scarcity. The purpose of the MLP is to increase the robustness of classification tasks, achieved through the effective mapping of robust SBERT representations to sentiment classes. Wu *et al.* [13] reported that fine-tuned BERT models demonstrate robust sentiment analysis. Typically, in standard BERT fine-tuning, the last classification layer is composed of a straightforward MLP, which is positioned on top of BERT.

Recent studies demonstrate that hybrid models with BERT, together with other deep models like MLP, CNN, and BiLSTM, still serve as the standard method, especially in sentiment analysis tasks, as they give the model the capability of distinguishing different linguistic aspects that might not be identified if they were working with pure BERT models. By combining BiLSTM with BERT, the encoding capabilities for sequential dependencies will be improved, giving the model the ability to comprehend order-sensitive information that usually lies within the transition of a sentence. Likewise, the addition of CNN with BERT helps in fortifying the model's capability in comprehending n-gram features, which become important for identifying discriminative phrases, sentiment cues, or entity triggers that are not easy to capture by using attention alone. Furthermore, the addition of an MLP classification head enables deeper nonlinear feature interactions that promote more expressive decision boundaries compared to a simple linear layer. In all, these hybrid approaches have been able to capitalize on BERT's strong contextual embeddings by enriching them with sequential modeling, local pattern detection, and nonlinear transformation capabilities, leading to improved performance on most NLP classification tasks. Therefore, this study proposes three hybrid models, WangchanBERTa-CNN, WangchanBERTa-BiLSTM, and WangchanBERTa-MLP, for multi-class sentiment classification of Thai restaurant reviews. The underlying algorithms utilized in these hybrid models are described as follows.

CNN is a leading text classification method, as it has been shown to learn local patterns and achieve state-of-the-art performance in most applications [32]. As shown in Fig.1, a CNN, theoretically, is a feed-forward neural network whose convolutional layers are tasked with creating feature maps by discovering informative patterns in the input text. The set of filters is applied in the convolutional layer over the input sequence to capture local n-gram features. Multiple filters with different sizes are often employed to capture various linguistic structures. Each filter generates a feature map that highlights the presence of certain patterns in the text. The feature maps are then reduced to lower dimensions by applying pooling operations, which preserve the most important information and reduce computational complexity. The most common approach in text classification is max pooling, which selects the highest activation value from each feature map. Following convolution and pooling, the feature maps are flattened and fed into one or more dense (fully connected) layers. The layers combine the extracted local features into a global representation of the input sequence. The output layer generally uses a softmax activation function (for multi-class classification) or a sigmoid function (for binary classification) [33, 34].

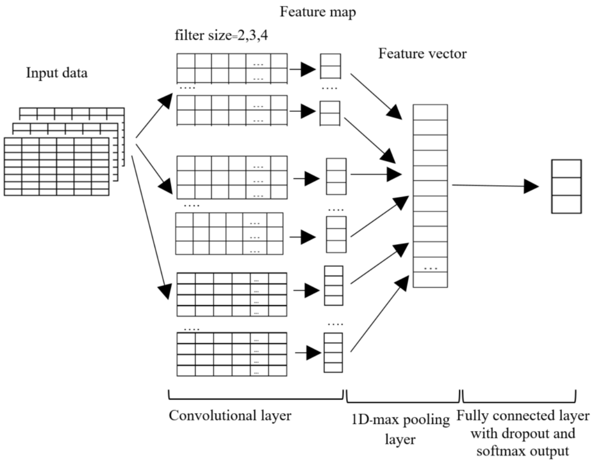

Fig.1: *The CNN architecture.*

BiLSTM is a more advanced version of the LSTM network that complements sequence modeling using contextual information from left and right contexts and future and past inputs. LSTM is a form of deep learning specifically focused on dealing with sequential data [35]. It is capable of processing long-term dependencies through selective remembering or forgetting. There are a few major components in an LSTM network: forget gate (f_t), input gate (i_t), candidate or input modulation gate, cell state (c_t), output gate (o_t), and hidden state (h_t). The forget gate decides what from the previous step to retain or discard in order to update the cell state. It calculates the present input (x_t) and the previous hidden state (h_{t-1}) using a Sigmoid activation, as given in (5), where W is the weight matrix, and b is the bias term. The input gate receives significant characteristics from the current input and the last hidden state, as given in (6). The input modulation gate produces candidate values for the cell state using the current input and the last hidden state, as indicated in (7). The new state of the cell is a result of a mixture of retained history information, which is controlled by the forget gate, and fresh information from the input and modulation gates, as shown in (8). The next hidden state is then computed by the output gate (9), the visible form of the model's learned sequence. The hidden state is the retained knowledge by the LSTM at the current time step, as denoted in (10).

In contrast to the normal LSTM that processes input in one pass, BiLSTM consists of two parallel LSTMs: one handling the sequence in the left-to-right direction and the other in the right-to-left direction. The forward and backward states are then concatenated later, which allows the model to maintain richer context representations [36]. Bidirectional architecture has emerged particularly well in several natural language processing tasks, such as sentiment analysis and machine translation, where it is imperative to capture the relationships between preceding and following words before and after [37].

$$f_t = sigmoid(W_f[h_{t-1}, x_t] + b_f) \tag{5}$$

$$i_t = sigmoid(W_i[h_{t-1}, x_t] + b_i) \tag{6}$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{7}$$

$$c_t = (f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t) \tag{8}$$

$$o_t = sigmoid(W_o[h_{t-1}, x_t] + b_o) \tag{9}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{10}$$

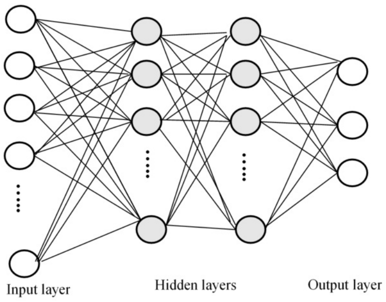

Fig.2: *The MLP architecture.*

MLP is one of the simplest deep learning networks. As shown in Fig.2, each layer has neurons that are fully connected with the next layer, where information is converted with a weighted sum and then followed by a nonlinear activation function. MLPs are capable of learning complex, nonlinear input-output mappings and are thus suitable for a variety of tasks, including classification, regression, and feature learning. Though basic compared to contemporary architecture, MLPs are still a core component of deep learning studies and practice[38]. MLPs typically perform better than traditional machine learning models. The baseline MLP with the introduction of neural feature-extraction layers (CNN, LSTM, BiLSTM) achieved major improvements well above baseline MLP models [39].

3. THE PROPOSED HYBRID MODELS

In this paper, we propose three hybrid models, called WangchanBERTa-CNN, WangchanBERTa-BiLSTM, and WangchanBERTa-MLP models.

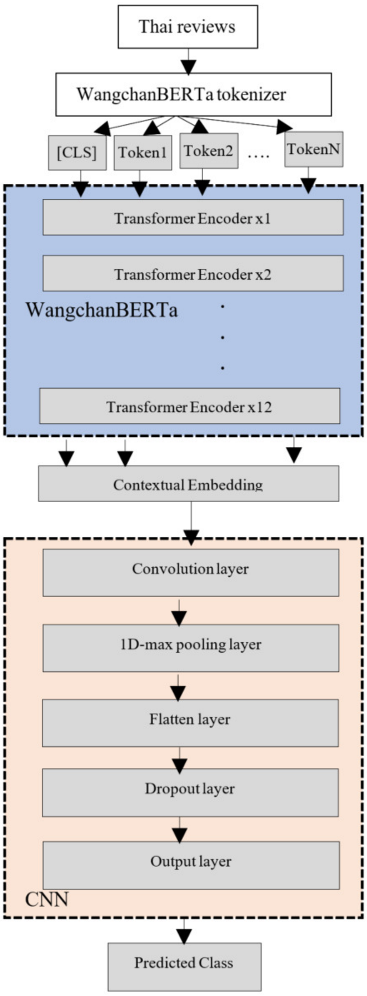

Fig.3: *The WangchanBERTa-CNN model.*

For the WangchanBERTa-CNN model, it employs WangchanBERTa with 12 layers, 768 hidden dimensions, and 12 attention heads [22] as an initial contextual encoder to achieve high-level hidden representations of Thai text, as contextual embedding. The embeddings pass through 1D convolutional filters with kernel sizes of 2, 3, and 4, each with 128 filters, enabling the model to capture local bi-gram, tri-gram, and four-gram features from the encoded sequence. A max-pooling process extracts the most significant features from each filter, and the resulting outputs are all concatenated to create a joint feature vector. Regularization is performed by dropouts, and linear classification generates sentiment labels. The interesting aspect is that the model takes advantage of deep semantic comprehension of WangchanBERTa with CNN's feature extraction to enhance performance on multi-class Thai sentiment analysis. Its power comes from the fusion of CNN's local pattern recognition and BERT's contextualized embedding at an efficient cost, and thus is suitable for short, noisy, or informal Thai text where fine-grained expressions are responsible for sentiment. The architecture of the WangchanBERTa-CNN model is represented in Fig. 3.

The WangchanBERTa-MLP model operates by first mapping the input text to contextualized embeddings that retain deep syntactic and semantic information using WangchanBERTa. Unlike convolutional or recurrent layers, it leverages the [CLS] token embedding, capturing the general meaning of the sentence, and feeds the [CLS] token embedding into an MLP made up of a fully connected layer, ReLU activation, dropout for regularization, and an output layer in order to classify. The concept here is that the model is taking advantage of BERT's strong contextual representation ability and applying the MLP as a simple classifier for projecting these embeddings into sentiment predictions. Its advantages are that it is light, efficient, and less prone to overfitting than more complicated architectures, but still performs well on Thai sentiment tasks through WangchanBERTa's pretrained strength. The architecture of the WangchanBERTa-MLP model is represented in Fig. 4.

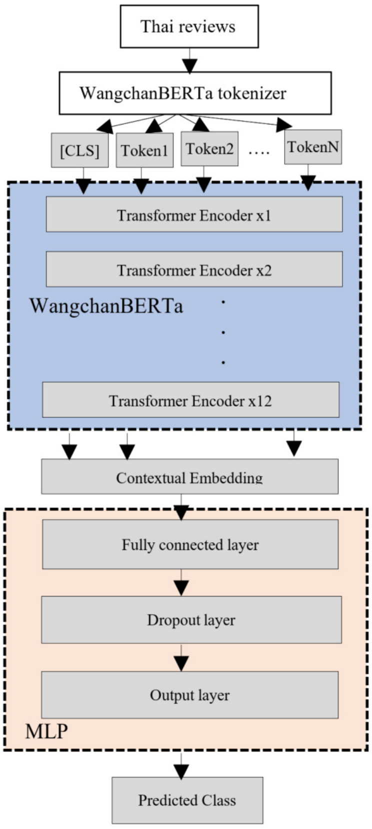

Fig.4: *The WangchanBERTa-MLP model.*

The WangchanBERTa-BiLSTM model utilizes WangchanBERTa to create contextual representations of each token in the input sentence. These representations are passed through a BiLSTM, reading from left to right and from right to left, allowing the model to effectively extract long-range dependencies and context flow in Thai text. The final timestep of the BiLSTM output pools the forward and backward states into a single rich representation, which is fed into a fully connected classifier to produce a sentiment prediction. The rationale here is that the BiLSTM enhances WangchanBERTa by picking up sequential and contextual dynamics throughout the sentence, which suits Thai since word order and context play an important role in deciding meaning. The advantages of this model are its capability to identify sequential dependencies, handle sophisticated linguistic structures, and enhance sentiment classification accuracy. The architecture of the WangchanBERTa-BiLSTM model is represented in Fig. 5.

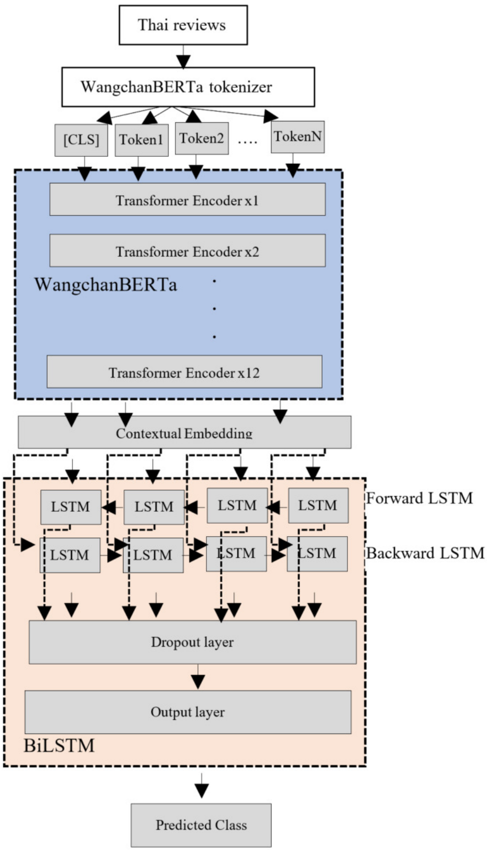

Fig.5: *The WangchanBERTa-BiLSTM model.*

4. EXPERIMENTAL SETUP AND RESULTS

In this study, a dataset derived from the Wongnai website was employed. The dataset includes a total of 3,981 positive, 3,811 neutral, and 415 negative reviews, as shown in Fig. 6. The analysis of the raw dataset indicates that most reviews contain fewer than 2,000 characters, as illustrated in Fig. 7, with overall lengths ranging from a minimum of 200 to a maximum of 9,960 characters. Looking at the text length distribution across sentiment labels, Fig. 8 shows that the maximum length of negative reviews is 2,446 characters, with most below 2,000 characters. Positive reviews are spread out further, reaching almost 10,000 characters, while the majority remains below 4,000 characters. Likewise, most neutral reviews are under 4,000 characters, with the longest reaching 4,950 characters.

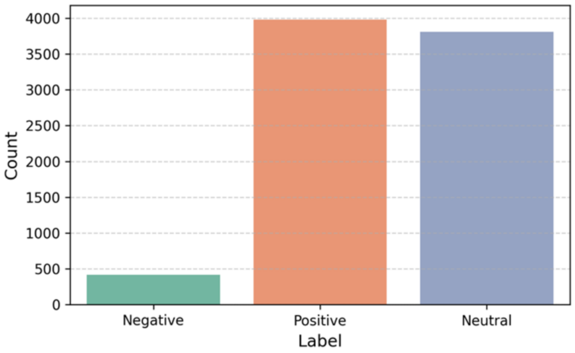

Fig.6: *Distribution of labels.*

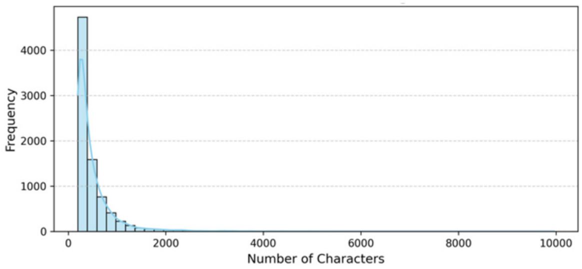

Fig.7: *Text length distribution in the dataset.*

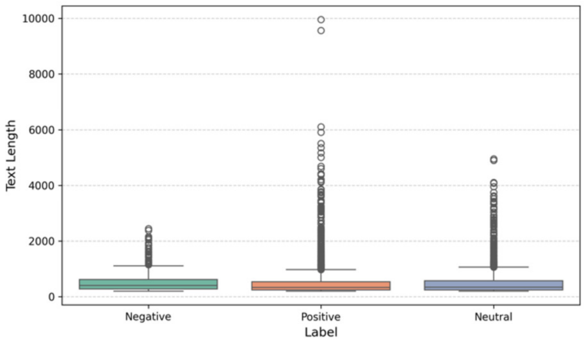

Fig.8: *Text length distribution per label.*

To create the word clouds, non-Thai characters and digits were removed from the reviews, and the texts were then segmented using the Next-Maximal-Matching tokenizer in PyThaiNLP to generate word clouds for each sentiment label, as illustrated in Fig. 9–Fig. 11. Across all labels, common terms such as ร้าน (restaurant), อร่อย (delicious), กิน (eat), and ทาน (eat) frequently appear. For positive reviews, words such as แนะนำ (recommend), ดี (good), รสชาติ (flavor), ลอง (try), ชอบ (like), and เมนู (menu) occur more often than in negative reviews; however, many of these terms also appear frequently in neutral reviews. This substantial lexical overlap makes distinguishing between positive and neutral reviews particularly challenging.

Fig.9: *Word cloud visualization for negative reviews.*

Fig.10: *Word cloud visualization for positive reviews.*

Fig.11: *Word cloud visualization for neutral reviews.*

The pre-processing phase involved removing any characters that were not part of the Thai script or numeric digits. Since the dataset was initially imbalanced, the SMOTE (Synthetic Minority Oversampling Technique) approach was applied to generate additional samples and achieve class balance. After applying the resampling technique, each sentiment category was represented by 3,981 reviews, resulting in a total of 11,943 reviews. The complete dataset was then split into three subsets, with 60% assigned for training, 20% for validation, and the remaining 20% for testing. In the case of BERT-based models such as RoBERTa, ALBERT, and XLM-RoBERTa, their corresponding tokenizers were used to segment the reviews into formats compatible with each model. For WangchanBERTa and the proposed hybrid models, the WangchanBERTa tokenizer was utilized, which is a SentencePiece sub-word tokenizer based on BPE (Byte-Pair Encoding).

In the experimental setup, a maximum sequence length of 128 tokens was set to control the input size. Training was performed with a batch size of 16, while the learning rate was set to 2e-5 using the AdamW optimizer and a weight decay of 0.01 to reduce overfitting. To enhance generalization, a dropout rate of 0.2 was applied. Both weight decay and dropout are regularization strategies. All the models were trained with 5 epochs to observe the optimal training point by considering the smallest gap between training and validation loss. The optimal point of each model was used for classification. The models were evaluated by accuracy, precision, recall, and F1-score.

In the first experiment, we aimed to evaluate whether WangchanBERTa outperforms other models in the BERT family for multi-class sentiment classification of Thai restaurant reviews. WangchanBERTa was compared against multilingual models that support the Thai language, including mBERT, ALBERT, and XLM-RoBERTa. The results of this comparison are presented in Table 2. Table 2 confirms that WangchanBERTa outperforms XLM-RoBERTa, ALBERT, and mBERT because it is trained specifically on large-scale Thai corpora, incorporates a Thai-optimized sub-word tokenizer, and captures language-specific contextual and semantic patterns more effectively than models trained across multiple languages. Therefore, the hybrid models are proposed based on WangchanBERTa.

Table 2: *The performance of extended BERT models (%).*

Polarity	Model	Wangchan BERTa	XLM-BERTa	ALBERT	mBERT
	Accuracy	**84.85**	83.05	63.16	75.85
Negative	Precision	93.63	94.34	95.17	90.11
	Recall	96.95	95.18	89.97	93.65
	F1-Score	**95.26**	94.76	92.50	91.85
Neutral	Precision	78.95	78.14	43.75	66.38
	Recall	75.19	69.42	00.88	67.04
	F1-Score	**77.02**	73.52	01.72	66.71
Positive	Precision	81.55	76.84	48.71	70.55
	Recall	82.57	84.68	98.75	67.12
	F1-Score	**82.05**	80.57	65.24	68.79

Fig. 12- Fig. 15 shows that the optimal training point of WangchanBERTa and WangchanBERTa-MLP is at epoch 3, while the optimal training point of WangchanBERTa-BiLSTM and WangchanBERTa-CNN appears to be at epoch 2.

Table 3 presents the performance comparison of four models: WangchanBERTa (baseline), WangchanBERTa-MLP, WangchanBERTa-CNN, and WangchanBERTa-BiLSTM on multi-class Thai sen-

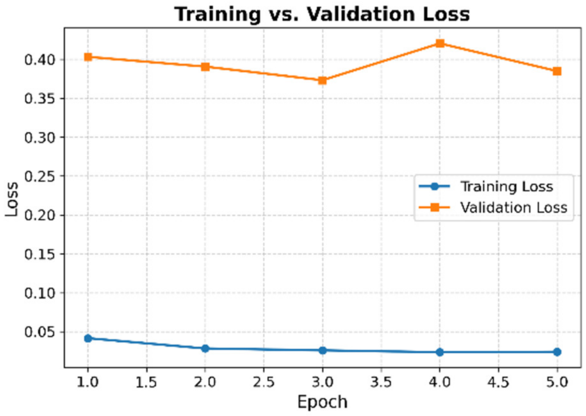

Fig.12: *Training and validation losses of WangchanBERTa.*

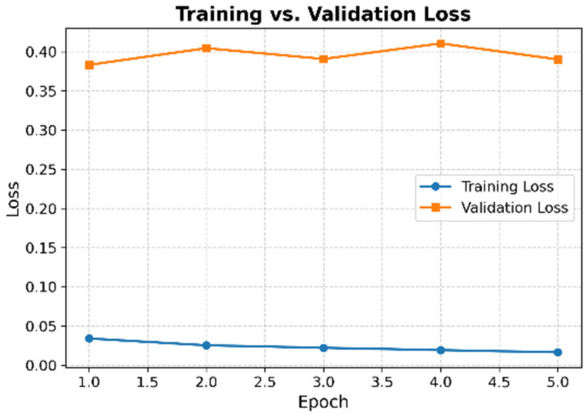

Fig.13: *Training and validation losses of WangchanBERTa-MLP.*

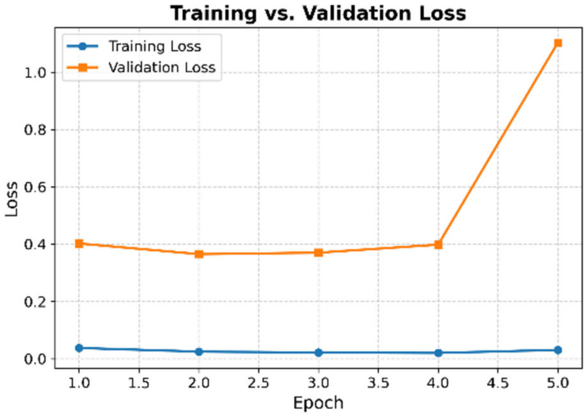

Fig.14: *Training and validation losses of WangchanBERTa-CNN.*

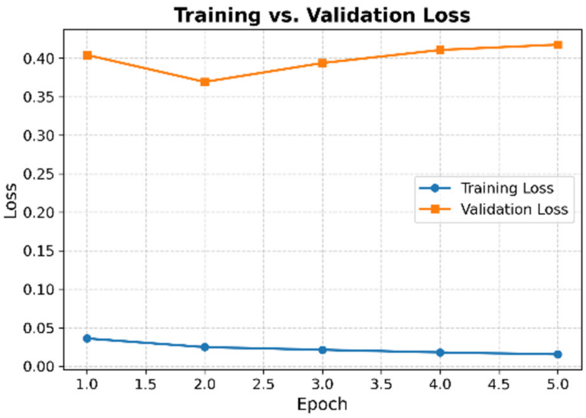

Fig.15: *Training and validation losses of WangchanBERTa-BiLSTM.*

timent classification (negative, neutral, and positive). In terms of overall accuracy, WangchanBERTa-BiLSTM achieved the highest score, 85.22%. For the negative class, all models performed consistently well, with F1-scores above 95%. WangchanBERTa-CNN achieved the highest precision (95.01%), while the baseline and WangchanBERTa-MLP showed strong recall (96.95%). In the neutral class, which is typically more challenging, WangchanBERTa-BiLSTM achieved the best balance with an F1-score of 77.30%. WangchanBERTa-MLP demonstrated relatively high precision (81.20%) but suffered from lower recall (71.43%), while WangchanBERTa-CNN showed a similar trade-off between precision (75.90%) and recall (76.57%). For the positive class, WangchanBERTa-BiLSTM again outperformed other models with the highest F1-score (82.65%), whereas the baseline achieved a comparable F1-score (82.05%).

Table 3: *Performance Comparison (%).*

Polarity	Model	Wangchan BERTa (baseline)	Wangchan BERTa-MLP	Wangchan BERTa-CNN	Wangchan BERTa-BiLSTM
	Accuracy	84.85	84.76	84.01	**85.22**
Negative	Precision	93.63	94.32	**95.01**	94.53
	Recall	**96.95**	**96.95**	96.57	96.57
	F1-Score	95.26	95.62	**95.78**	95.54
Neutral	Precision	78.95	**81.20**	75.90	80.11
	Recall	75.19	71.43	**76.57**	74.69
	F1-Score	77.02	76.00	76.23	**77.30**
Positive	Precision	**81.55**	78.79	81.10	80.83
	Recall	82.57	**86.05**	79.08	84.56
	F1-Score	82.05	82.26	80.08	**82.65**

In Fig. 16, the confusion matrix of the WangchanBERTa model shows that the model sometimes interprets neutral sentiment as positive and positive sentiment as neutral. Specifically, the model misclassified 146 neutral reviews as positive and 140 positive reviews as neutral. Similarly, the WangchanBERTa-MLP model misclassified 182 neutral reviews as positive (as shown in Fig. 17), which is the largest number of misclassifications among the models, although the error in classifying positive reviews as neutral was

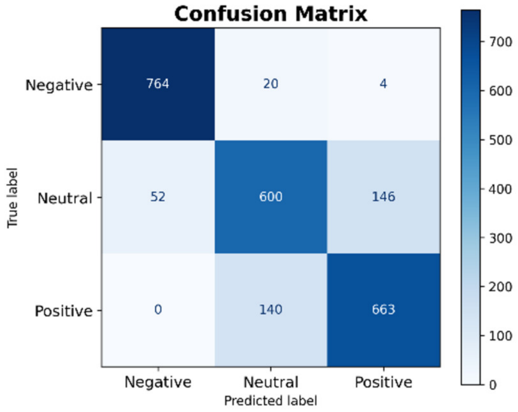

Fig.16: *Confusion matrix of WangchanBERTa.*

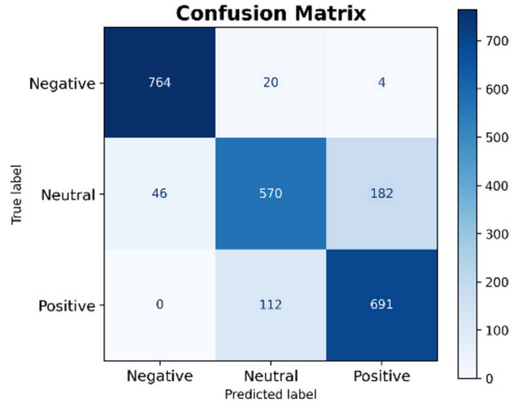

Fig.17: *Confusion matrix of WangchanBERTa-MLP.*

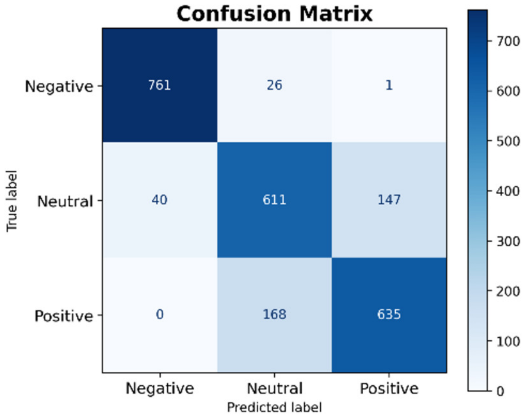

Fig.18: *Confusion matrix of WangchanBERTa-CNN.*

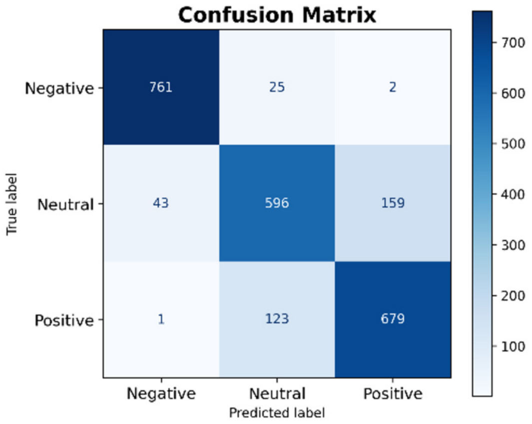

Fig. 19: *Confusion matrix of WangchanBERTa-BiLSTM.*

reduced. The WangchanBERTa-CNN model, on the other hand, produces the largest number of misclassified positive reviews as neutral, as shown in Fig. 18. The confusion matrix of the WangchanBERTa-BiLSTM model (Fig. 19) indicates that it reduces the error in classifying positive reviews as neutral compared to WangchanBERTa, but it still suffers from the problem of misclassifying neutral reviews as positive.

Overall, these results indicate that integrating BiLSTM with WangchanBERTa leads to the most robust performance across Thai multi-sentiment classes, particularly by improving the classification of neutral and positive reviews. As shown in Fig. 16- Fig.19, although the WangchanBERTa-BiLSTM model achieved better performance than the baseline in predicting positive reviews, it continued to misclassify a considerable portion of neutral reviews as positive, like the other models.

5. DISCUSSION

The main purpose of this study was to examine the effectiveness of the hybrid WangchanBERTa with deep learning models (BiLSTM, CNN, and MLP) for multi-class sentiment classification of Thai restaurants' reviews. From the study, the results show that hybrid WangchanBERTa with deep learning models can improve the classification of sentiment scenarios for Thai restaurants' reviews, especially incorporating a sequential modeling layer, such as BiLSTM. Hybrid WangchanBERTa and BiLSTM significantly improve overall performance when compared to the BERT-based models. Among all models, the WangchanBERTa with BiLSTM produced the highest accuracy, 85.22%, which is better than WangchanBERTa (84.85%). Simultaneously, the highest F1-scores were produced in the neutral sentiment, with a value of 77.30% as compared with WangchanBERTa, with a value of 77.02%, as well as the positive sentiment, with a value of 82.65% compared with WangchanBERTa with a value of 82.05%. Among the hybrid models, the highest F1-score was produced in the negative sentiment, with a value above 95% when compared with the single BERT-based models. Therefore, negative sentiment is more readily distinguishable in Thai text when using the proposed hybrid models.

Despite these performance gains, challenges remain in accurately distinguishing neutral from positive sentiment. Confusion matrix analyses indicate that all the hybrid models, including WangchanBERTa-BiLSTM, still misclassify a notable number of neutral reviews as positive and vice versa. This limitation likely stems from the subtle and context-dependent nature of sentiment expression in Thai, where neutral reviews often contain mildly positive cues that can be overinterpreted by the models.

6. CONCLUSION

This study proposed three hybrid deep learning models, WangchanBERTa-MLP, WangchanBERTa-CNN, and WangchanBERTa-BiLSTM, for multi-class sentiment classification of Thai restaurant reviews. Using a balanced dataset created through SMOTE, the models were trained and compared against a WangchanBERTa baseline. The experimental results show that the integration of BiLSTM with WangchanBERTa yields the most robust overall performance, achieving the highest accuracy (85.22%). In particular, WangchanBERTa-BiLSTM provided a better balance in handling the neutral class, which is often the most challenging in multi-class sentiment analysis. It achieves the highest F1-scores for classifying neutral and positive reviews. Despite all these advances, all models, including WangchanBERTa-BiLSTM, still misclassified neutral reviews as positive, which means that differentiation of fine sentiment expression is still a limitation. These results again support the necessity of marrying context language models with sequence-sensitive architecture to capture the complexity of Thai language sentiment.

Future work includes integrating attention mechanisms to help the models focus on the most important words in a sentence, as well as fine-tuning models such as WangchanBERTa-BiLSTM to achieve a deeper understanding of Thai sentiment. Another promising direction is exploring aspect-based sentiment analysis, which goes beyond predicting only positive, negative, or neutral sentiment for an entire review. For example, in restaurant reviews, the model could analyse the sentiment of aspects such as food, service, and price. This approach provides more detailed insights and is highly useful for Thai-language applications. Generalizing the model to other Thai domains also poses an interesting challenge. This involves applying the model beyond the current dataset to areas such as hotel reviews, product reviews, and social media comments to determine whether it can maintain strong performance across different types of Thai text. In addition, combining several different models (e.g., WangchanBERTa + CNN + BiLSTM) into a single ensemble system is another valuable direction, as ensemble methods often achieve higher accuracy by leveraging the strengths of multiple models rather than relying on just one.

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AUTHOR CONTRIBUTIONS

Conceptualization, methodology, validation, and formal analysis: Panida Songram; writing—original draft preparation: Panida Songram and Khanabhorn Kawattikul; writing—review and editing: Panida Songram, Suchart Khummanee, Khanabhorn Kawattikul, and Nittaya Muangnak. All authors have read and agreed to the published version of the manuscript.

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