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RESEARCH ARTICLE

Multilabel-Thai Text Classification with Transformer-Rnn in Thai Banking Classification

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ABSTRACT

This research presents a novel approach to multilabel Thai text classification within the banking sector using a hybrid Transformer-RNN model. The study focuses on enhancing the accuracy and efficiency of document categorization in Thai language, addressing the complexities inherent to diverse banking documents. The model integrates BERT for pre-training to leverage contextual embeddings and incorporates an RNN to capture sequential dependencies in the text data. Evaluation of the model's performance was conducted using precision, recall, and F1 score metrics over a 10-fold cross-validation setup. The hybrid Transformer-RNN model demonstrated robust performance across multiple evaluation metrics. Specifically, it achieved an average precision of 0.823, recall of 0.817, and F1 score of 0.815. These results indicate the model's efficacy in accurately predicting multiple labels associated with various types of Thai banking documents. Comparative analysis against LSTM, CNN, BERT, and Transformer (Encoder-Only) models further validates the superiority of the proposed approach in handling complex multilabel classification tasks in the Thai banking domain. This research underscores the potential of hybrid Transformer-RNN models in advancing multilabel text classification capabilities, particularly in specialized domains like Thai banking. The findings highlight significant improvements in classification accuracy and model robustness, contributing to enhanced document management, regulatory compliance, and customer service within the banking industry. Future research directions could explore ensemble learning techniques, domain adaptation strategies, and the integration of domain-specific knowledge bases to further enhance the model's performance and applicability in real-world scenarios.

INTRODUCTION

Text classification serves as a fundamental task in natural language processing (NLP), offering applications ranging from sentiment analysis and spam detection to specialized domains such as legal document classification and medical report categorization (Liu et al. 2019). In the banking sector, accurate text classification plays a pivotal role across various applications including customer service automation, fraud detection, compliance monitoring, and risk management. Efficiently categorizing and managing vast amounts of textual data can significantly enhance operational efficiency and decision-making processes within banking institutions.

The Thai language presents unique challenges for text classification due to its linguistic characteristics. Unlike many other languages, Thai lacks explicit word boundaries, written consecutively without spaces, complicating the tokenization process (Kongsumran. 2021). Additionally, Thai's tonal nature with five distinct tones and its complex script forms like diacritics and vowel positioning further add to the complexity of NLP tasks. These linguistic intricacies demand sophisticated models capable of effectively handling Thai language nuances.

Moreover, banking documentation encompasses specialized terminology, regulatory jargon, and diverse document types including transaction records, compliance reports, customer inquiries, and financial statements. Multilabel classification becomes essential as a single document often relates to multiple categories simultaneously, necessitating models capable of assigning multiple relevant labels accurately (Maia et al. 2021).

Traditional text classification approaches such as Naive Bayes and Support Vector Machines (SVM) have been widely applied but often fall short in Multilabel scenarios and handling Thai language complexities (Kaewvichit et al. 2024). Recent advancements in deep learning, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown promise in improving classification accuracy. CNNs excel in capturing local dependencies, while RNNs, especially Long Short-Term Memory (LSTM) networks, are effective in modeling sequential data.

However, standalone CNNs and RNNs have limitations. CNNs may struggle with long-range dependencies due to their limited receptive field, while RNNs can face challenges in training on very long sequences and issues like vanishing gradients (Yin et al. 2017). Transformers, introduced by Vaswani et al. (2017), have revolutionized NLP with their ability to capture long-range dependencies and contextual relationships through self-attention mechanisms. Models like BERT (Devlin et al. 2019), a pre-trained Transformer, have further improved performance by leveraging extensive pre-training on diverse corpora (Wang et al. 2024).

Despite their strengths, Transformers alone may not fully exploit the sequential nature of text data, particularly in domain-specific contexts such as banking where information order is crucial. Integrating Transformers with RNNs in a hybrid architecture offers a promising solution by combining global context capture from Transformers with sequential processing capabilities of RNNs (Zhao et al. 2022). This hybrid approach aims to develop a robust model tailored for multilabel classification of Thai banking documents.

The primary objective of this research is to develop and evaluate a hybrid Transformer-RNN model specifically designed for Multilabel classification of Thai banking documents. By leveraging Transformer's capability to capture contextual nuances and RNN's proficiency in handling sequential dependencies, this study aims to address the challenges posed by the Thai language and the specific requirements of banking texts. By achieving these objectives, this research seeks to contribute to advancements in Thai text classification methodologies and provide a robust framework applicable to other domain-specific multilabel classification tasks.

LITERATURE REVIEW

Background and Related Work

Text Classification

Text classification is a foundational task in natural language processing (NLP), involving the categorization of textual data into predefined classes or categories (Sebastiani 2002). Traditional machine learning techniques such as Naive Bayes, Support Vector Machines (SVM), and decision trees have been widely employed for text classification due to their effectiveness in certain scenarios (Sebastiani 2002).

Multilabel Classification

Multilabel classification extends the task of single-label classification by allowing instances to be associated with multiple labels simultaneously (Tsoumakas and Katakis 2007). Common approaches include Binary Relevance and Classifier Chains, which treat each label independently or in a predefined sequence but may not effectively capture label dependencies (Tsoumakas and Katakis 2007).

Machine Learning for Multilabel Classification

Machine learning methods for multilabel classification adapt single-label classifiers or ensemble techniques to handle multiple labels per instance effectively (Tsoumakas and Katakis 2007). These methods focus on exploiting label correlations and optimizing performance metrics tailored to multilabel scenarios.

Deep Learning for Multilabel Classification

Deep learning has significantly advanced multilabel classification by utilizing neural networks to learn complex feature representations and capture intricate label dependencies. Models incorporating Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and attention mechanisms have shown notable improvements in handling multilabel data (Kim 2014; Liu et al. 2016).

Transformer Models

Transformer models introduced by Vaswani et al. (2017) have transformed NLP tasks by leveraging self-attention mechanisms to capture contextual dependencies across input sequences effectively (Vaswani et al. 2017). These models have achieved state-of-the-art performance in various language-related tasks, surpassing traditional sequential models.

Transformer Models for Multilabel Classification

Transformer models have been adapted for multilabel classification tasks by incorporating mechanisms to handle multiple labels per instance efficiently. These adaptations often involve modifications in model architecture and training objectives to accommodate the complexity of multilabel data (Kim 2014; Devlin et al. 2018).

Thai Language Processing

Thai language processing presents unique challenges due to its non-segmented nature, complex tonal system, and rich morphology (Aroonmanakun. 2002). Traditional methods for Thai NLP often rely on dictionary-based approaches and rule-based segmentation, which may struggle with handling complex linguistic structures.

Application to Banking Sector

In the banking sector, text classification is crucial for applications such as customer service automation, fraud detection, compliance monitoring, and risk assessment. Banking documents often contain legal and financial terminology, necessitating accurate and efficient text classification systems capable of handling domain-specific nuances.

METHODOLOGY

Dataset Description

The dataset used for this study consists of 24,500 Thai banking messages. These messages encompass various text types within the banking domain, including customer feedback. Each message is annotated with multiple labels, indicating different categories or topics relevant to the

Thai banking sector. The multilabel nature of the dataset poses a challenge, as each message can belong to multiple categories simultaneously.

Table 1: Label Analysis

Sample Thai Text Extracted	**Sample Text Extracted**	**Label Analysis by Experts**
พนักงานที่เคาเตอร์ใช้เวลาทำไม่นานแต่ พนักงานที่ยืนแจกคิว (ผู้หญิง) ไม่เข้าใจความต้องการลูกค้าเลยให้บัตรคิวผิดช่อง ทำให้ต้องรอคิวนานมาก	Employees at the counter spend very little time, but the employee who distributes the queue (female) misunderstands the customer's needs, resulting in queue cards being issued incorrectly. This causes a long wait.	Timing, Service Time, Staff, Communication & Understand customer needs, Staff, Human Error
บริการดีเยี่ยม ยิ้มแย้มแจ่มใสรวดเร็วทันใจ	Excellent service, bright smiles, quick and prompt.	Timing, Service Time, Staff, Manner
พนักงานดำเนินการให้อย่างรวดเร็ว การบริการข้อมูลอื่นๆ ดีเยี่ยม ประทับใจที่มาใช้บริการรู้สึกได้ว่าน้อง ๆ พนักงานเอาใจใส่ลูกค้าดูแลดีที่สุดรู้สึกประทับใจจริงๆค่ะ	The staff handles transactions quickly, provides excellent service, and impresses customers who come to use the service, feeling that the staff really cares for customers well.	Timing, Service Time, Staff, Manner, Staff, Knowledge

Preprocessing

Thai Language Processing

Processing Thai text involves several crucial steps to prepare the data for input into the model:

Word Segmentation: Due to the lack of explicit word boundaries in Thai text, word segmentation is essential. The **newmm** tokenizer from the PyThaiNLP library is used, which leverages dictionary-based and machine learning techniques to accurately split text into meaningful tokens.

Normalization: Normalization includes converting all characters to a standard format, handling different encodings, and removing punctuation and special characters. This step ensures consistency across the dataset.

Tokenization: The segmented and normalized text is then tokenized using subword tokenization techniques, such as byte-pair encoding (BPE) or WordPiece tokenization. These techniques handle out-of-vocabulary words and reduce vocabulary size by representing frequent word parts as tokens.

Model Architecture

Transformer-RNN Hybrid Model

The proposed model combines the strengths of Transformer and Recurrent Neural Network (RNN) architectures to handle the multilabel classification task effectively. Combining Transformer and RNN models for multilabel classification brings together the strengths of both architectures, resulting in several significant advantages. The Transformer component, with its self-attention mechanism, excels at capturing complex, long-range dependencies between words, which is crucial for accurately predicting multiple labels from a single text. This ability to weigh the importance of different words in context enhances the model's understanding of the relationships within the text, making it particularly effective in scenarios where texts are associated with multiple labels.

In recent advancements in natural language processing (NLP), combining Transformer and Recurrent Neural Network (RNN) models has proven to be a powerful approach for multilabel classification tasks. Transformers are renowned for their ability to capture long-range dependencies and contextual relationships within text through self-attention mechanisms. On the other hand, RNNs, particularly Long Short-Term Memory (LSTM) networks, excel in capturing sequential dependencies and temporal dynamics in text data. By integrating these models, we leverage the strengths of both architectures to improve classification performance in complex scenarios where a single text can be associated with multiple labels.

Transformer Encoder: The Transformer encoder, inspired by BERT (Devlin et al. 2018), captures contextual relationships and long-range dependencies within the text using self-attention mechanisms. This allows the model to understand the significance of each word in relation to the entire input sequence.

Recurrent Neural Network (RNN): An RNN layer, specifically Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells (Hochreiter and Schmidhuber 1997; Cho et al. 2014), is employed to further process the encoded representations from the Transformer. The RNN captures sequential dependencies and temporal information that are crucial for understanding the flow of banking documents.

Fumbler Mechanism: Inspired by the concept of ensemble learning, the fumbler mechanism integrates predictions from both Transformer and RNN components. It fuses the contextual strengths of the Transformer with the sequential learning capabilities of the RNN, aiming to enhance predictive accuracy and robustness.

Multilabel Classification Layer: The final output layer comprises sigmoid-activated neurons, where each neuron corresponds to a label. The sigmoid activation function outputs probabilities indicating the presence of each label, facilitating multilabel classification (Hochreiter and Schmidhuber 1997; Cho et al. 2014).

The model architecture is mathematically described as follows:

Transformer Encoder:

$$\mathbf{H} = \mathrm{TransformerEncoder}(\mathbf{X})$$

where $\mathbf{X}$ is the input token embeddings and $\mathbf{H}$ is the output contextual embeddings.

RNN Layer:

$$\mathbf{H}_{\mathrm{RNN}} = \mathrm{RNN}(\mathbf{H})$$

where $\mathbf{H}_{\mathrm{RNN}}$ represents the sequentially processed embeddings.

Output Layer:

$$\mathrm{y} = \sigma(\mathrm{W}\mathbf{H}_{\mathrm{RNN}} + \mathrm{b})$$

where σ denotes the sigmoid activation function W and b are trainable parameters, and y represents the probability scores for each label.

Raining Strategy

Pre-training and Fine-tuning

BERT Pre-training Approach: The BERT (Bidirectional Encoder Representations from Transformers) model, introduced by by Devlin et al. (2018), is pre-trained using a self-supervised learning approach. The pre-training involves two tasks: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP).

Masked Language Modeling (Mlm):

$$\mathrm{L}_{MLM} = -\sum_{t \in \mathrm{M}} \log P\left(x_t \middle| X_{/\mathrm{M}}\right)$$

Where M is the set of masked token positions, x_t is the original token, and $X_{\backslash \mathrm{M}}$ is the input sequence with masked tokens replaced by a special [MASK] token. The objective is to predict the masked tokens based on their context.

Next Sentence Prediction (NSP):

$$\mathrm{L}_{NSP} = -\left(y \log P\left(\mathrm{IsNext} \middle| \mathbf{X}_{\mathrm{A}}, \mathbf{X}_{\mathrm{B}}\right) + (1-y) \log P\left(\mathrm{NotNext} \middle| \mathbf{X}_{\mathrm{A}}, \mathbf{X}_{\mathrm{B}}\right)\right)$$

Where $\mathbf{X}_{\mathrm{A}}$ and $\mathbf{X}_{\mathrm{B}}$ are two input sentences, and y is a binary label indicating whether $\mathbf{X}_{\mathrm{B}}$ follows $\mathbf{X}_{\mathrm{A}}$ in the original text.

Fine-tuning for Multilabel Classification

After pre-training, the BERT model is fine-tuned on the specific multilabel Thai text classification task:

Loss Function

The binary cross-entropy loss function is used to train the model, as it is suitable for multilabel classification tasks:

$$\mathrm{L} = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \log\left(\hat{y}_i\right) + \left(1 - y_i\right) \log 1 - \hat{y}_i \right]$$

where N is the number of labels, y_i is the ground truth label, and $\hat{y}_i$ is the predicted probability.

Evaluation Metrics

Performance Metrics

Evaluating the performance of a multilabel classification model involves measuring how accurately the model predicts each label. The primary metrics used are precision, recall, and F1 score, which are calculated for each label independently and then averaged. These metrics provide insight into the model's ability to identify relevant labels (precision), detect all relevant labels (recall), and balance precision and recall (F1 score).

Precision: Precision measures the proportion of true positive predictions among all positive predictions made by the model. It indicates how many of the predicted labels are actually relevant.

$$precision_j = \frac{TP_j}{\left(TP_j + FP_j\right)}$$

where:

TP_j is the number of true positives for label j.

FP_j is the number of false positives for label j.

The macro-averaged precision, which is the average precision across all labels, is given by:

$$precision_{macro} = \frac{1}{L}\sum_{j=1}^{L} Precision_j$$

where L is the total number of labels.

Recall: Recall measures the proportion of true positive predictions among all actual positive instances. It indicates how many of the relevant labels the model successfully identified.

For a single label j, recall is defined as:

$$\text{Recall}_j = \frac{TP_j}{\left(TP_j + FN_j\right)}$$

where: FN_j is the number of false negatives for label j.

The macro-averaged recall is given by:

$$\text{Recall}_{\text{macro}} = \frac{1}{L}\sum_{j=1}^{L} Recall_j$$

F1 Score: The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. It is particularly useful when there is an uneven class distribution or when we need to balance precision and recall.

For a single label j, the F1 score is defined as:

$$\text{F1}_\text{j} = \frac{2 \times precision_j \times recall_j}{\left(recall_j + precision_j\right)}$$

The macro-averaged F1 score is given by:

$$\text{F1}_{\text{macro}} = \frac{1}{L}\sum_{j=1}^{L} F1_j$$

Hamming Loss: The fraction of labels that are incorrectly predicted. It is defined as:

$$\text{Hamming Loss} = \frac{1}{\text{N} \cdot \text{L}}\sum_{i=1}^{N}\sum_{j=1}^{L} 1\left(y_{ij} \neq \hat{y}_{ij}\right)$$

where N is the number of samples, L is the number of labels, and 1 is the indicator function.

RESULTS

The results of the multilabel Thai text classification using the Transformer-RNN model in the Thai banking domain are presented in this section. The evaluation metrics include precision, recall, and F1 score, computed over a 10-fold cross-validation setup. These metrics assess the model's effectiveness in accurately predicting multiple labels associated with various types of banking message.

Evaluation Metrics

Precision

Precision measures the proportion of predicted positive instances that are actually positive. For multilabel classification, precision is calculated independently for each label and then averaged across all labels.

The average precision ($precision_{macro}$) across the 10 folds was **0.823**. This indicates that, on average, 82.3% of the predicted labels were correct across all labels.

Recall

Recall measures the proportion of actual positive instances that were correctly predicted by the model. Similar to precision, recall is computed for each label independently and then averaged.

The average recall (Recall_{macro}) across the 10 folds was **0.817**. This means that, on average, the model correctly identified 81.7% of all actual positive labels.

F1 Score

The F1 score is the harmonic mean of precision and recall, providing a single metric that balances both measures. Like precision and recall, F1 score is calculated for each label and then averaged across all labels.

The average F1 score ($\mathrm{F1}_{macro}$) across the 10 folds was **0.815**. This metric combines precision and recall into a single value, reflecting the model's overall performance in multilabel classification tasks.

Comparative Analysis

To benchmark the performance of our hybrid model, we compared it against several baseline models, including LSTM, CNN, BERT, and a Transformer encoder-only model. The results are summarized in Table 2.

Table 2 Performance Comparison of Hybrid Model with Baseline Models

Model	**Precision**	**Recall**	**F1 Score**
LSTM	0.780	0.785	0.782
CNN	0.755	0.762	0.758
BERT	0.810	0.803	0.806
Transformer (Encoder-Only)	0.795	0.800	0.797
Hybrid Transformer-RNN	0.823	0.817	**0.**815

The results indicate that our hybrid Transformer-RNN model outperforms the baseline models across all evaluated metrics. Specifically, it achieves higher precision, recall, and F1 score, demonstrating its effectiveness in capturing both contextual information from Transformer-based embeddings and sequential dependencies from the RNN component.

Precision: The hybrid model's precision of 0.823 indicates that it accurately predicts relevant labels more often than the baselines.

Recall: With a recall of 0.817, the model effectively identifies a large proportion of actual positive instances.

F1 Score: The F1 score of 0.815 reflects a balanced performance in terms of precision and recall, crucial for multilabel classification tasks.

These findings highlight the advantage of integrating Transformer and RNN architectures for complex multilabel classification tasks in the Thai banking domain. The hybrid approach leverages Transformer's ability to capture global dependencies and RNN's capability to model sequential patterns, resulting in superior performance compared to standalone architectures.

CONCLUSION

In this paper, we presented a hybrid Transformer-RNN model tailored for multilabel classification of Thai banking texts. Our approach addresses the unique linguistic challenges of the Thai language and the specialized requirements of banking message. The model leverages the strengths of Transformers for capturing contextual dependencies and RNNs for sequential data processing, resulting in significant improvements over traditional models.

The results from our experiments indicate that the model achieves superior performance compared to baseline approaches, including LSTM, CNN, BERT, and Transformer (Encoder-Only). Specifically, the hybrid model excelled in precision, recall, and F1 score, showcasing its ability to effectively categorize various banking message into relevant labels.

The key contributions of this research include:

Model Effectiveness: The hybrid Transformer-RNN model leverages Transformer's capability to learn contextual embeddings and RNN's strength in capturing sequential dependencies, thereby enhancing classification accuracy.

Performance Metrics: Through rigorous evaluation using 10-fold cross-validation, we demonstrated that the model consistently outperforms traditional methods in multilabel classification tasks, particularly in the domain-specific context of Thai banking.

Practical Implications: The application of this model can significantly improve document management, regulatory compliance, and customer service within the Thai banking industry, offering a robust solution for automated document categorization.

Future research directions may explore ensemble learning techniques, domain adaptation strategies, and the integration of domain-specific knowledge bases to further enhance the model's performance and scalability. By advancing multilabel text classification methodologies in Thai language processing, this study contributes to broader applications in natural language understanding and document management systems.

This research underscores the potential of hybrid Transformer-RNN models in advancing multilabel text classification tasks, particularly in complex and specialized domains like banking, paving the way for enhanced efficiency and accuracy in document processing and analysis.

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