An Exploratory Study of BiGRU Architectures for Thai-Language Crisis Sentiment Classification

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Abstract- The rapid dissemination of information during public health crises, such as the COVID-19 pandemic, necessitates robust automated systems to monitor public sentiment. This research presents an exploratory study of various Bidirectional Gated Recurrent Unit (BiGRU) architectures specifically tailored for Thai-language sentiment classification. Using a balanced dataset of Thai news tweets, the study systematically investigated eight distinct BiGRU configurations—ranging from simple bidirectional layers to deep-stacked architectures—to identify optimal frameworks for crisis management. The experimental results indicate that a streamlined architecture featuring a 256-unit bidirectional layer followed by a single 128-unit dense layer delivered the most effective performance among the tested configurations. This specific model achieved an accuracy of 0.7334 and an f1-score of 0.7324. Further analysis of the classification performance reveals high precision in identifying negative and neutral sentiments, whereas the positive class remains a significant classification challenge. While this study demonstrates that BiGRU models offer a computationally efficient and accurate solution for Thai text analysis, there remains significant potential to push these performance gains even further. The results suggest that a transition toward hybrid designs—specifically the Hybrid BiGRU (GRU-Conv1D-BiGRU) model—represents the next logical step in this research line. The integration of convolutional layers allows for the extraction of fine-grained features that single-model architectures often overlook. Ultimately, this work establishes a solid, validated foundation for developing the real-time sentiment monitoring tools that remain essential for decision-makers navigating large-scale social crises.

Index Terms- Sentiment Analysis, Bidirectional Gated Recurrent Unit (BiGRU), Thai Natural Language Processing, Crisis Management, COVID-19 Social Media Analysis.

I. INTRODUCTION

The recent waves of global health crises, most notably the COVID-19 pandemic, have really driven home how vital it is to process information quickly and accurately during a crisis. Today, social media platforms like Twitter (now X) act as real-time barometers for public sentiment, offering a massive stream of data that can—and should—guide governmental and health responses. However, trying to make sense of this data is no small task. The sheer volume of posts, combined with the linguistic complexity of a language like Thai, creates major hurdles for manual analysis. Because Thai has such unique structural characteristics, we need more sophisticated automated tools to truly understand what the public is saying.

1.1 Research Problems

Despite the advancements in Deep Learning, several challenges persist in the domain of Thai-language sentiment classification during crises:

- *Linguistic Complexity*: Thai is a character-based language without explicit word boundaries, making sentiment detection more difficult compared to space-delimited languages.
- *Model Optimization*: While various architectures exist, there is a lack of systematic exploration regarding which specific BiGRU configurations yield the highest accuracy for Thai news sentiment.
- *Neutral Class Ambiguity*: Current models often struggle to distinguish objective news reporting (neutral) from subjective sentiment (positive/negative) within short-form social media texts.

.1.2 Research Objectives

This study aims to address these issues through the following objectives:

- *Architectural Benchmarking*: To systematically evaluate eight distinct BiGRU architectures (Models A–H) to determine the optimal balance between model depth and classification accuracy.
- *Performance Analysis*: To analyze the effectiveness of these models across three sentiment polarities—negative, neutral, and positive—using a balanced dataset of Thai-language COVID-19 news tweets.
- *Foundation for Hybrid Systems:* To establish a performance baseline that justifies the development of more advanced Hybrid BiGRU (GRU-Conv1D-BiGRU) models in subsequent research.

By addressing these objectives, this research provides a validated framework for automated sentiment monitoring, offering a scalable tool for practitioners to gauge public sentiment during periods of high-intensity news cycles.

II. LITERATURE REVIEW

The field of sentiment analysis has shifted significantly from lexicon-based approaches to Deep Learning (DL) models. DL models capture complex semantic relationships within text more effectively [1]. This review examines current research concerning BiGRU architectures and hybrid systems, particularly within the context of Thai-language processing and crisis management.

2.1 Deep Learning for Thai Sentiment Analysis

Thai-language sentiment analysis presents unique challenges because it is a character-based language without explicit word boundaries [1]. Recent studies demonstrate that Bidirectional Gated Recurrent Units (BiGRU) are highly effective for this task [2]. Research indicates that BiGRU models with attention mechanisms often outperform standard RNN and CNN variants when classifying Thai online documents [3]. Specifically, using the WangchanBERTa model and skip-gram word embeddings can enhance Thai sentiment classification accuracy, with some models reaching F1-score as high as 0.92 [3].

The implementation of Word Embeddings via Keras layers allows for mapping Thai tokens into a dense vector space, which is critical for capturing semantic nuances in the absence of spaces. Studies on Thai COVID-19 news tweets have established a baseline for classifying sentiment across multiple classes ranging from positive to negative [1].

2.2 BiGRU Architectures in Crisis Management

During global crises like the COVID-19 pandemic, real-time sentiment monitoring is crucial for maintaining social resilience and improving media literacy [4]. BiGRU deep learning classifiers have shown high efficiency in detecting misinformation and sentiment polarity in large-scale health data, achieving an F1-scores of 0.92 in specific configurations [4].

The bidirectional nature of these units allows them to capture context from both the past and future of a sequence, which is essential for understanding news-based tweets [5]. Exploratory studies on BiGRU configurations suggest that streamlined, well-tuned architectures can achieve optimal results without the computational overhead of overly deep models [2, 5]. Information enhancement within bidirectional layers has been shown to significantly reduce error rates in polarity detection compared to unidirectional models.

2.3 Evolution Toward Hybrid Models (GRU-Conv1D-BiGRU)

There is a growing consensus in recent literature that hybrid models are the key to overcoming the structural limitations found in single-architecture designs [1, 6]. By combining Convolutional layers (Conv1D) with BiGRU layers, researchers can leverage the best of both worlds: CNNs excel at pulling meaningful features from raw text, while the BiGRU handles the long-term sequential flow [3]. In fact, more advanced setups like the BiGRU-Att-HCNN have already demonstrated clear accuracy jumps over standard bidirectional baselines [6]. These hybrid models are particularly useful for the messy, imbalanced datasets often found in real-world tasks, as they can extract multi-scale features through parallel standard and dilated convolutions [6]. Furthermore, the gating mechanisms within these structures have proven highly effective at solving the 'vanishing gradient' problem that often plagues deep learning projects [2].

III. RESEARCH METHODOLOGY

The methodology for this study follows a structured deep learning pipeline to evaluate eight distinct BiGRU configurations for Thai-language crisis sentiment classification [1, 3, 7, 8]. The framework is organized into four primary phases: data acquisition, specialized Thai text preprocessing, architectural design, and performance evaluation.

3.1 Data Acquisition and Labeling

The research focuses on public sentiment during the COVID-19 pandemic using social media data.

- Data Source: A balanced dataset of Thai-language tweets was curated to capture a representative sample of public reactions to crisis-related news.
- Sentiment Polarity: Following established standards in social media analysis, each text was categorized into three classes: Positive, Neutral, or Negative [3, 8].
- Ground Truth: To ensure high-quality training data, labels were established based on researcher consensus, focusing on the distinction between factual news reporting and subjective opinion.

3.2 Thai Text Preprocessing Pipeline

Thai text requires specialized handling due to its lack of word delimiters and complex script [1, 7].

- Noise Reduction: Initial cleaning involves removing noise such as URLs, usernames (@), hashtags (#), and special symbols that do not contribute to sentiment.
- Word Segmentation: Because Thai is a character-based language, a tokenization process is applied to segment continuous character strings into meaningful word units [3, 7].
- Feature Enhancement: The text is further refined by removing common stop words and applying Part-of-Speech (POS) tagging to identify sentiment-carrying adjectives and verbs.
- Vectorization: Each token is converted into a numerical representation using an Embedding Layer. This maps unique words to dense vectors in a continuous space, allowing the model to recognize semantic similarities between different terms [9].

3.3 Architectural Framework (Models A–H)

The core of this exploratory study is the systematic comparison of eight Bidirectional Gated Recurrent Unit (BiGRU) architectures.

- BiGRU Layers: Unlike standard GRUs, the BiGRU architecture processes data in both forward and backward directions, capturing context from both the past and future of a sentence [2, 5].
- Model Scaling: The research tested configurations ranging from single-layer BiGRUs to deeper networks with stacked

Dense layers and varying dropout rates to prevent overfitting [5, 10].

- The Optimal Model (Model F): Among the tested variations, the study identified a specific configuration—featuring a 256-unit bidirectional layer followed by a 128-unit dense layer—as the most effective for this dataset.

3.4 Evaluation and Diagnostics

The effectiveness of each architecture was assessed using a comprehensive suite of metrics to identify strengths and weaknesses in classification [1, 3].

- Performance Metrics: Models were evaluated based on overall Accuracy, Precision, Recall, and the F1-score.
- Class-Specific Analysis: Special attention was given to the F1-score for the Neutral class, which literature identifies as the most challenging category in Thai sentiment tasks [11, 12].
- Error Visualization: A confusion matrix was generated for the best-performing models to visualize specific misclassification patterns, such as the overlap between neutral reporting and negative sentiment [3, 5].

IV. RESULTS

4.1 Performance of the BiGRU models

4.1.1. Performance Comparison of BiGRU Configurations

To determine the optimal baseline for Thai-language sentiment analysis, eight distinct BiGRU configurations (A–H) were evaluated using a balanced dataset of COVID-19 news tweets. The comparative performance metrics, including accuracy, precision, recall, and f1-score, are summarized in Table 1.

Table 1: Performance Comparison of 8 BiGRU Configurations.

Model	Accuracy	Precision	Recall	f1-score
A	0.6821	0.6835	0.6821	0.6775
B	0.6696	0.6686	0.6696	0.6689
C	0.6658	0.6664	0.6658	0.6661
D	0.6533	0.6604	0.6533	0.6491
E	0.6283	0.6250	0.6283	0.6160
F	0.7334	0.7348	0.7334	0.7324
G	0.6220	0.6205	0.6220	0.6209
H	0.6834	0.6823	0.6834	0.6824

4.1.2 Analysis of Findings

As illustrated in Table 1, Model F emerged as the superior architecture, achieving the highest accuracy of 0.7334 and a balanced f1-score of 0.7324. While configurations such as Model A and Model H showed competitive performance with f1-scores nearing 0.68, Model F provided a substantial performance gain of approximately 5% over the next best configuration.

The data suggests that the specific balance of hyperparameter tuning and layer depth found in Model F is particularly well-suited for the bidirectional dependencies of the Thai language. It seems that this configuration manages to pick up on semantic nuances that other models missed. Interestingly, when we look at the shifts in performance across Models D, E, and G, a clear pattern emerges: simply adding complexity isn't enough. Without the right level of regularization, such as dropout, increasing the depth of the network actually leads to diminishing returns in how well the model classifies sentiment.

The robust f1-score of Model F establishes it as a highly capable baseline for the subsequent hybrid model investigation. These results suggest that the BiGRU architecture is particularly effective at processing the sentiment polarity of crisis-related news in the Thai language, providing the necessary empirical evidence to move forward with the GRU-Conv1D-BiGRU hybrid variants.

4.2 Architectures of the BiGRU models

The study systematically investigates eight architectural variations of the Bidirectional Gated Recurrent Unit (BiGRU). This is to identify the optimal configuration for Thai sentiment classification. As illustrated in Figure 1, each model follows a multi-layered sequential structure designed to capture complex linguistic patterns from news tweets.

4.2.1 Core Layer Components

All models share a common foundation consisting of three primary stages:

- Embedding Layer: Converts input text into dense vector representations with an output shape of (None, 1335, 1335).
- Bidirectional GRU Layer: Processes sequences in both forward and backward directions to maintain contextual information from both the past and future. The number of units vary across models, with Models A-B utilizing 128 units and Models C-H utilizing 256 units.
- Dense Layer: Following the bidirectional layer, these fully connected layers perform higher-level feature extraction. Models A–B employ a primary dense layer of 64 units, while Models C–H utilize a larger 128-unit dense layer.
- Dropout Layer: Across the eight tested architectures, the dropout rates were varied within a range of 0.2 to 0.5 to identify the optimal level of regularization for the Thai crisis dataset. The highest-performing configuration, Model F, utilized a dropout rate of 0.2.
- Output Layer: Every configuration utilizes a Softmax activation function in the final dense layer to provide a probability distribution over the three target classes: Negative, Neutral, and Positive.

4.2.2 Structural Variations (Models A–H)

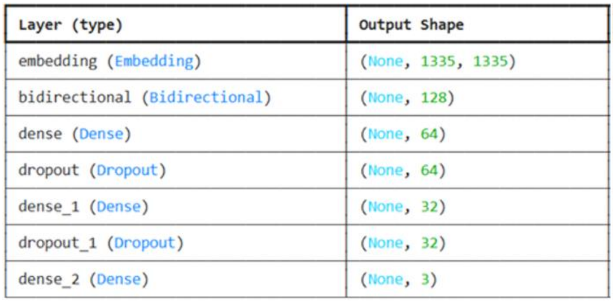
The complexity of the architectures increases progressively through the addition of dense and dropout layers to manage feature extraction and prevent overfitting:

- Baseline Models (A & B): These utilize a single BiGRU layer followed by two dense layers.
- Standard Architectures (C, D, & E): These increase the BiGRU hidden units and expand the depth of the dense network to capture more intricate features.
- The Optimized Configuration (Model F): Unlike the others, Model F utilizes a streamlined three-layer dense structure (128, 64, and 3 units) immediately following the BiGRU layer. This specific reduction in depth, combined

with 256 BiGRU units, resulted in the highest accuracy recorded in this study (0.7334%).

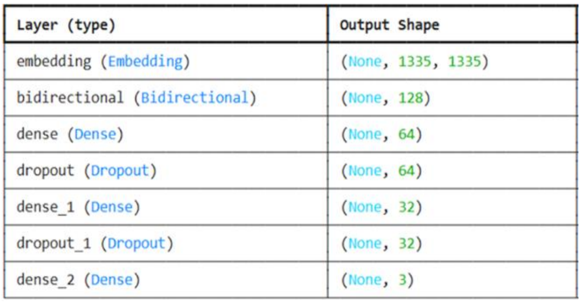
- Deep Configurations (G & H): These represent the most complex variations, incorporating up to three dropout layers and four dense layers to test the limits of the sequential model depth.

Model A



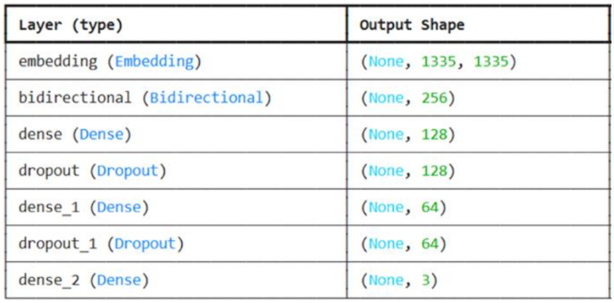
Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 128)
dense (Dense)	(None, 64)
dropout (Dropout)	(None, 64)
dense_1 (Dense)	(None, 32)
dropout_1 (Dropout)	(None, 32)
dense_2 (Dense)	(None, 3)

Model B



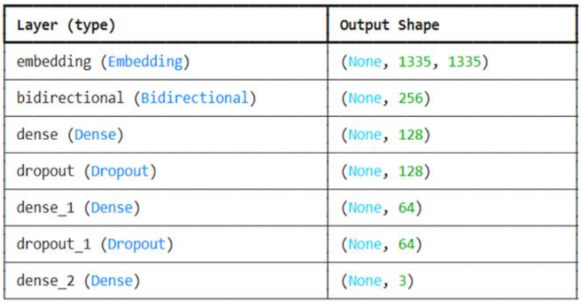
Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 128)
dense (Dense)	(None, 64)
dropout (Dropout)	(None, 64)
dense_1 (Dense)	(None, 32)
dropout_1 (Dropout)	(None, 32)
dense_2 (Dense)	(None, 3)

Model C



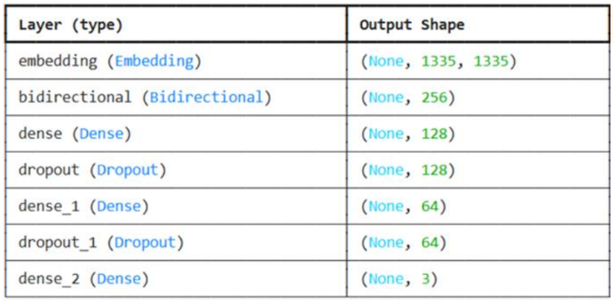
Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 256)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 64)
dropout_1 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 3)

Model D



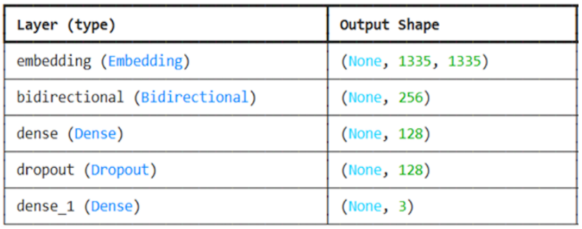
Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 256)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 64)
dropout_1 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 3)

Model E



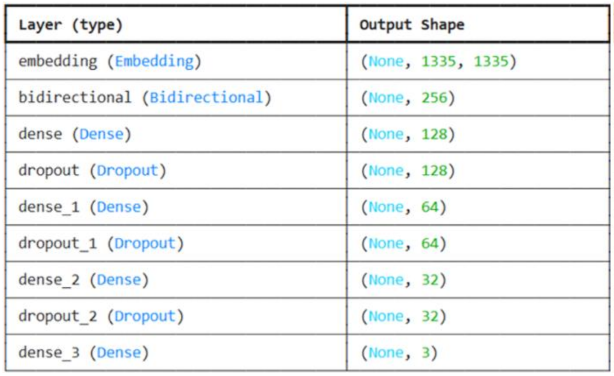
Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 256)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 64)
dropout_1 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 3)

Model F



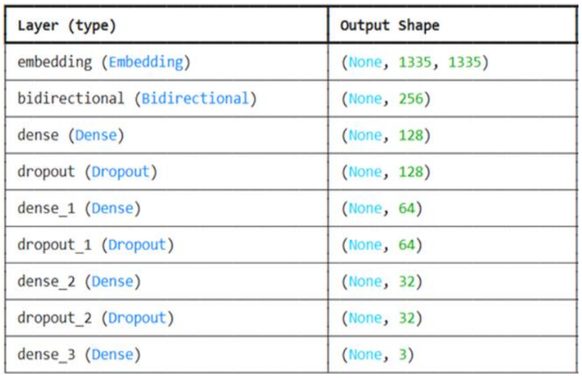
Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 256)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 3)

Model G



Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 256)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 64)
dropout_1 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 32)
dropout_2 (Dropout)	(None, 32)
dense_3 (Dense)	(None, 3)

Model H



Layer (type)	Output Shape
embedding (Embedding)	(None, 1335, 1335)
bidirectional (Bidirectional)	(None, 256)
dense (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_1 (Dense)	(None, 64)
dropout_1 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 32)
dropout_2 (Dropout)	(None, 32)
dense_3 (Dense)	(None, 3)

Figure 1: Layer Architecture of the BiGRU Models.

4.3 Training and Validation Analysis

The learning behavior of the champion BiGRU model (Model F) was monitored over 15 epochs to evaluate stability and convergence. Figure 2 and Figure 3 illustrate the accuracy and loss trajectories for both the training and validation sets. As shown in Figure 2, the training accuracy (blue line) exhibits a steady and rapid ascent, surpassing 80% by the 4th epoch and peaking near

96% by epoch 11. The validation accuracy (red line) follows a similar upward trend, reaching its optimal plateau of approximately 75% around the 8th epoch. The consistent gap between the training and validation curves indicates that while the model successfully learned the underlying patterns of Thai news sentiment, it maintained a reasonable level of generalization.

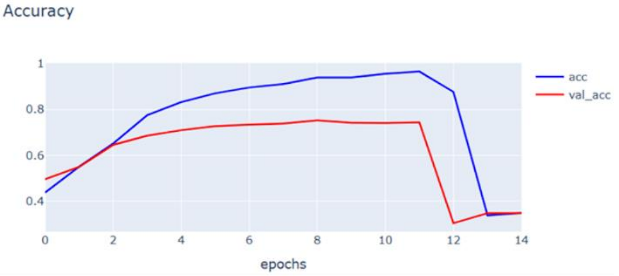


Figure 2: Accuracy Curves for the Best-Performing BiGRU Model.

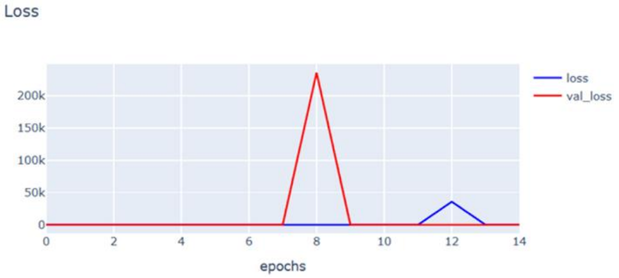


Figure 3: Loss Curves for the Best-Performing BiGRU Model.

However, Figure 3 reveals a significant volatility spike in validation loss at epoch 8, followed by a training loss spike at epoch 12. These fluctuations, paired with the sharp decline in accuracy seen in the final epochs, suggest that the model began to overfit the training data or encountered a gradient instability. Consequently, the weights from epoch 8 were selected as the final model state, as they represent the point of peak validation performance and optimal error minimization before the onset of instability. This data-driven selection ensures the BiGRU baseline remains robust for comparative analysis with the hybrid architectures.

4.4 Per-Class Performance Analysis

To further evaluate the diagnostic capability of the BiGRU architectures, a per-class classification report was generated for all eight configurations across the Neutral, Positive, and Negative categories. The detailed metrics are presented in Table 2.

Table 2: Per-Class Classification Report for the Best BiGRU Model

Model	Accuracy	Neutral Class			Positive Class			Negative Class		
		Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
A	0.6821	0.6961	0.5185	0.5943	0.6656	0.7374	0.6997	0.6903	0.5185	0.5943
B	0.6696	0.6322	0.6296	0.6309	0.6517	0.6259	0.6385	0.7172	0.7482	0.7324
C	0.6658	0.6185	0.6337	0.6260	0.6594	0.6547	0.6570	0.7153	0.7050	0.7101
D	0.6533	0.6441	0.4691	0.5429	0.5871	0.7518	0.6593	0.7481	0.7158	0.7316
E	0.6283	0.5987	0.3745	0.4608	0.5988	0.7194	0.6536	0.6741	0.7590	0.7148
F	0.7334	0.7286	0.6296	0.6755	0.6765	0.7446	0.7089	0.7986	0.8129	0.8057
G	0.6220	0.5132	0.4815	0.4968	0.6095	0.6619	0.6400	0.7153	0.7050	0.7101
H	0.6834	0.6473	0.5967	0.6210	0.6540	0.6799	0.6667	0.7413	0.7626	0.7518

A comparative analysis of the results reveals that the models consistently achieved their highest performance within the Negative Class. Model F, the overall top-performing configuration, reached a peak F1-score of 0.8057 for negative sentiment, supported by a precision of 0.7986 and a recall of 0.8129. This indicates that the bidirectional nature of the GRU is highly effective at capturing the linguistic markers and intensity typically associated with negative crisis-related reporting in Thai tweets.

In contrast, performance in the Neutral Class was lower across all configurations, with Model F achieving an F1-score of 0.6755. The relatively lower recall scores for neutral sentiment—such as 0.6296 for Model F and as low as 0.3745 for Model E—suggest that neutral news content often shares overlapping vocabulary with positive or negative categories, leading to classification ambiguity.

While performance for the Positive Class held steady—specifically with Model F's F1-score at 0.7089—the results reveal a deeper trend. It appears that while a standard BiGRU handles clear polarities well, it consistently struggles with the subtle nuances of neutral text. This difficulty in resolving neutral ambiguity directly informed our decision to develop the hybrid architectures discussed next. By integrating convolutional layers, we aim to capture the specific local features that simple recurrent models often miss, hopefully drawing a sharper line between neutral comments and truly polarized content.

4.5 Performance Breakdown: Best BiGRU Model

The confusion matrix (Figure 4.) reveals how accurately the model classified sentiment across three categories (labeled Negative, Neutral, and Positive).

4.5.1 Core Successes (True Positives)

The model shows a strong ability to identify the correct classes, as seen on the main diagonal:

- Class Negative: 226 correct classifications (the highest performance).
- Class Positive: 207 correct classifications.
- Class Neutral: 153 correct classifications.

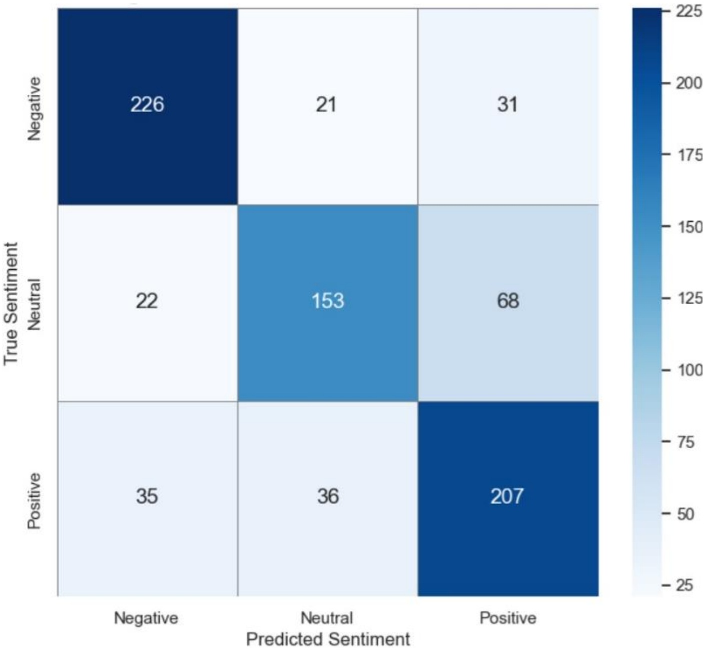


Figure 4: Confusion Matrix for the Best BiGRU Model.

4.5.2 Analysis of Misclassifications

The matrix highlights exactly where the model is losing accuracy:

- Class Neutral → Class Positive: This is the most frequent error, with 68 instances of Class Neutral being incorrectly labeled as Class Positive.
- Class Positive Confusion: Class Positive is occasionally mistaken for Class Negative (35 times) or Class 1 (36 times).
- Class Negative Accuracy: This category is the most distinct for the model, with only minor leakage into Class Positive (31 times) and Class Neutral (21 times).

4.5.3 Key Observation

The most significant challenge for this specific model iteration is distinguishing between Neutral and Positive class. Further refinements to the feature extraction process, coupled with an expanded training dataset, are expected to yield higher overall accuracy..

V. CONCLUSION

The evaluation of eight BiGRU architectures (Models A–H) for Thai-language sentiment analysis reveals that Model F is the most effective configuration for this task. Model F achieved the highest overall performance across all key metrics, including an accuracy of 0.7334, a precision of 0.7348, and an f1-score of 0.7324.

5.1 Architectural Insights

Optimal Depth: Model F utilizes a streamlined architecture featuring a Bidirectional layer (256 output shape) followed by a single Dense layer (128 units) before the final output, suggesting that excessive depth in the dense layers (as seen in Models G and H) does not necessarily improve performance for this specific dataset.

Performance Stability: Models G and E were the least effective, with accuracies of 0.6220 and 0.6283 respectively, indicating that more complex layer stacking can lead to diminishing returns or overfitting in Thai sentiment classification.

5.2 Sentiment Class Performance

Negative Class Superiority: For most models, the Negative Class consistently yielded the highest f1-scores, with Model F reaching 0.8057 for this category.

Neutral Class Challenges: The Neutral Class proved the most difficult to classify accurately. The neutral classification often yields the lowest recall and f1-scores across the suite (e.g., Model E's recall of 0.3745).

5.3 Confusion Matrix Analysis

The confusion matrix for the best-performing model shows strong diagonal alignment, particularly for Class Negative (226 correct) and Class Positive (207 correct), while Class Neutral exhibited more significant overlap with the other categories.

In summary, this study identifies Model F as the benchmark BiGRU architecture for Thai sentiment analysis, providing a balanced and highly accurate tool for monitoring public sentiment during crisis events.

VI. FUTURE RESEARCH

Building upon the benchmarks established by the BiGRU 8-model suite, future research will focus on the development and optimization of Hybrid BiGRU architectures, specifically the GRU-Conv1D-BiGRU configuration. Incorporating a convolutional layer to an RNN offers a path toward capturing more intricate linguistic patterns.

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