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A Hybrid Method Based on CRITIC Method and Machine Learning Models for Effective Fake News Detection in Thai Language

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Abstract

Fake news has emerged as a pervasive issue within the modern information ecosystem, leading to widespread dissemination of misinformation and erosion of trust. This paper introduces a novel hybrid approach for effectively detecting fake news in the Thai language by combining the CRITIC method with multiple machine learning models. The initial step involves collecting Thai-language fake news data from websites. Subsequently, the data undergoes a preprocessing phase. In the second step, the preprocessed data is used for validation through three basic machine learning models, namely, Naive Bayes, Decision Tree, and K-Nearest Neighbors. In the third step, the accuracy results from these three models are employed to calculate the significance weights of each model using the CRITIC method. In the final step, predictions are recalculated using the proposed method. The proposed method achieves an 83.37% accuracy, surpassing Naive Bayes (80.83%), Decision Tree (80.37%), and K-Nearest Neighbors (75.75%). This indicates a significant enhancement in performance, with the proposed method outperforming the established models by up to 7.62%. Consequently, the proposed method can enhance the performance of fake news detection in Thai language by utilizing an ensemble of the original models. A significant advantage of this approach is its simplicity coupled with high efficacy. It is postulated that this method can be adapted for detecting fake news in other languages as well.

Keywords: *CRITIC method; Decision Tree; ensemble machine learning; fake news detection; K-Nearest Neighbors; Naive Bayes*

1. Introduction

With the ongoing transformation of the digital ecosystem, there has been an unsettling surge in the propagation of 'fake news' – deliberately crafted misinformation with extensive ramifications on political, social, and individual levels (Allcott, & Gentzkow, 2017; Lazer et al., 2018). This dilemma transcends the Anglophone world, manifesting peculiar hurdles in varied linguistic terrains, including the Thai language. Thai's unique linguistic attributes, such as the lack of spaces between words, non-segmented structure, and distinct scripts, intensify the challenges associated with implementing automated text analytics and natural language processing - essential instruments for countering fake news (Kongwan, Kamaruddin, & Ahmad, 2022). The peculiar traits of Thai language necessitate bespoke strategies to effectively identify and mitigate fake news. Wang et al. (2023) have highlighted the promise of employing advanced techniques like deep learning and knowledge graphs to address the Thai fake news dilemma. Still, they also emphasize the specific impediments posed by the intricate linguistic constructs of Thai. Consequently, crafting sophisticated detection mechanisms attuned to the intricacies of the Thai language is of paramount and urgent necessity.

Machine learning has emerged as a potential answer to the fake news problem, with recent advancements in natural language processing enabling the analysis of vast data sets with speed and accuracy, thereby allowing for real-time fake news detection (Shu et al., 2017). Nevertheless, these technologies are far from infallible and are limited by the quality of their training data. They can also be deceived by sophisticated deceptive techniques, emphasizing the need for continuous improvement and the exploration of novel detection methods (Zhou, & Zafarani, 2018). Regarding Thai text, machine learning applications for fake news detection remain a largely untapped field. Thai language's unique linguistic and cultural aspects offer both challenges and opportunities for devising effective fake news detection algorithms. By harnessing the power of machine learning, we can potentially build models capable of accurately classifying and detecting fake news in Thai text, thereby contributing significantly to global efforts aimed at curbing the proliferation of digital misinformation (Zampieri et al., 2019).

Criterion Importance Through Intercriteria Correlation (CRITIC) has emerged as an effective methodology for tackling the convolutions of multi-criteria decision-making problems (Zeleny, 2012; Wichapa, Khokhajaikiat, & Chaiphet, 2021; Nasawat et al., 2021). This strategy, which focuses on discerning the relative significance of criteria and establishing their correlations, helps foster a thorough understanding of the decision-making context (Opricovic, & Tzeng, 2004). Previous studies leveraging the CRITIC method have demonstrated enhanced precision and efficacy in the decision-making process by incorporating the interdependencies among criteria (Tzeng, & Huang, 2011). Empirical research across various domains, including project management (Xu, & Yang, 2001), supplier selection (Chen, 2000), sustainability assessment (Lai, Liu, & Hwang, 1994), and performance evaluation (Wang, & Lee, 2009), has underscored CRITIC's effectiveness. These studies have revealed the ability of the CRITIC method to offer a methodical and robust framework for tackling multi-criteria decision-making issues, facilitating more informed decision-making and yielding reliable outcomes. Given these findings, the integration of the CRITIC method in addressing multi-criteria decision-making challenges stands to advance the decision sciences significantly, supporting more robust and informed decision-making practices. The adaptation of this method in our study represents a crucial extension of its applications, addressing the critical need for effective fake news detection algorithms in the unique context of the Thai language.

Based on the comprehensive literature survey conducted, it is evident that machine learning techniques have been extensively employed to identify and mitigate the proliferation of falsified information. Prominent machine learning models, such as Naive Bayes (NB), Decision Trees (DT), and K-Nearest Neighbors (K-NN), have been widely utilized in text classification tasks, including the detection of fake news and sentiment analysis. These models are characterized by their simplicity and ease of implementation as supervised machine learning algorithms. Consequently, the concept of combining the NB, DT, and K-NN algorithms presents itself as an excellent approach to effectively address the issue of detecting fake news. Furthermore, conventional hybrid approaches commonly rely on voting mechanisms, which often disregard the importance of individual model performance by assigning equal weights to all models. Departing from previous research efforts that neglected the weight of each model in the fusion process, this study introduces an innovative methodology that takes into account the accuracy-based weights of each model during training. While the CRITIC method has gained considerable attention in addressing Multi-Criteria Decision Making (MCDM) problems, its application in conjunction with machine learning for text classification remains limited. Hence, this research aims to present a pioneering approach by synergistically incorporating all three models with the CRITIC method to effectively detect and combat the dissemination of fake news, ultimately enhancing the overall performance of fake news detection.

The subsequent sections of the paper are organized as follows. Section 2 presents an overview of the related works in the field, providing a comprehensive understanding of the existing literature. In Section 3, the proposed method is elaborated upon, detailing its key components and the approach taken. The experimental evaluations, including the methodology and the obtained results, are presented in Section 4. Finally, Section 5 concludes the paper by summarizing the key findings and discussing potential avenues for future research.

2. Related Works

Detecting fake news in Thai text is one of the natural language processing techniques applied to filter news before being disseminated on online social networks. Chumnankit, and Siriborvorn-ratanakul (2022) introduced a method for detecting fake news in the Thai language using natural language processing techniques. They specifically classified headlines that had been pre-filtered on the Anti-Fake News Center Thailand. In this process, they selected news related to health products, totaling 339 headlines for classification. During the testing process, they compared words or phrases that matched fake news to identify the class. The experimental results showed an overall accuracy of 80% for headline classification and 84.17% when selectively considering nouns and classifiers.

Pandey et al. (2022) focused on detecting fake news in online media using machine learning models. The preprocessing process included stop word removal and stemming. Five machine learning models, namely K-Nearest Neighbors, Support Vector Machine, Decision Tree, Naïve Bayes, and Logistic Regression, were compared.

The application of machine learning strategies in the realm of fake news detection has grown significantly. For instance, Gururaj et al. (2022) employed numerous machine learning algorithms, such as K-NN, Naive Bayes, and Decision Tree, to discover the superior accuracy of the Decision Tree model in detecting medical misinformation. In a similar vein, a comparative study by Alghamdi, Lin, and Luo (2022) found that BERTbase and RoBERTabase outperformed other models when solely focusing on news text analysis.

Several research efforts have explored the use of ensemble machine learning models in identifying fake news. A notable example is the study by Liu, and Wu (2018), where they introduced an innovative approach for the early detection of fake news on social media platforms. This method involves analyzing the routes through which news stories spread, using a combination of recurrent and convolutional networks to examine both broad trends and detailed variations in user behavior along these paths. In this approach, each news story's spread is represented as a complex time series, with each data point reflecting the attributes of a user involved in disseminating the story. This model has demonstrated superior performance over existing fake news detection methods, achieving remarkable accuracy rates of 85% on Twitter and 92% on Sina Weibo within just five minutes of a story's initial spread. This represents a significant improvement in both speed and accuracy compared to traditional models. Additionally, Jlifi, Sakrani, and Duvallet (2022) developed an advanced Soft Three-Level Voting Model specifically for distinguishing COVID-19 related fake news, which has shown to outperform other similar classification systems.

On the front of multi-criteria decision-making problems, the CRITIC method has been effectively utilized in a variety of contexts. For instance, Ahmad, Khan, and Saeid (2023) successfully integrated the CRITIC method with DEMATEL techniques and the MABAC method to identify occupational hazards. Further, Al-shami, and Mhemdi (2023) introduced a novel class of orthopair fuzzy sets, "(2,1)-Fuzzy sets," for handling multi-criteria decision-making problems. Similarly, Wang, and Lee (2009) proposed a unique method for multi-criteria decision-making based on rough sets and a fuzzy measure, demonstrating the influence of different reduction methods corresponding to different rules on the decision result.

Despite the widespread use of machine learning techniques for detecting and mitigating fake news, relying solely on a single model for text classification may not yield optimal results Murugesan, and Pachamuthu (2022), Alghamdi, Lin, and Luo (2023). To enhance text classification, previous studies have suggested combining different models Khanmohammadi, and Rezaei (2021) and Jlifi, Sakrani, and Duvallet (2022). However, these methods tend to overlook the differing performance of individual models by assigning equal weights to each model. Unlike these traditional approaches, the present study introduces a novel methodology that considers the significance of each model's weight based on its accuracy during the training process. Although the CRITIC method has seen significant use for Multi-Criteria Decision Making (MCDM) (Wang, & Lee, 2009; Ahmad, Khan, & Saeid, 2023; Al-shami, & Mhemdi, 2023), its potential in tandem with machine learning for text classification remains untapped. This study aims to bridge the existing knowledge gap by combining the CRITIC method with various machine learning models to enhance the overall accuracy of fake news detection.

3. Methodology

This research presents a fusion of three machine learning models using the CRITIC method to enhance the fake news detection performance for Thai language text. The process consists of five steps: data collection and preprocessing, feature extraction, model training and validation for the machine learning models, implementation of the CRITIC method to generate criteria weights for each model and testing the proposed model. The proposed framework is shown in Figure 1.

3.1 Data collection and preprocessing

Data collection and preprocessing are crucial steps in researching fake news detection in Thai text. This section describes the methodology employed for data collection and the preprocessing techniques applied to ensure the quality and suitability of the dataset.

The methodology began with gathering a comprehensive dataset of Thai text from the Anti-Fake News Center Thailand (https://www.antifakenewscenter.com), an initiative by the Ministry of Digital Economy and Society. This dataset, which included a broad spectrum of news articles labeled as either true or fake, was sourced from various websites, social media platforms, and online forums. Emphasis was placed on ensuring diverse representation in news topics and sources. The dataset, which includes both verified false information and corroborated factual content, was accumulated over a period from March 2020 to June 2021. The final dataset for the research consisted of 2,162 entries, with 1,803 entries of fake news and 359 entries of true news. Since the data was collected from a complaint-receiving website regarding fake news for verification, the data in this research is an imbalanced dataset. The entries in the dataset cover an extensive array of subjects, comprising, among others, COVID-19 (629 entries), financial markets (12 entries), national security (120 entries), government policies (454 entries), health products (539 entries), natural disasters (78 entries), narcotics (6 entries), and economic matters (324 entries).

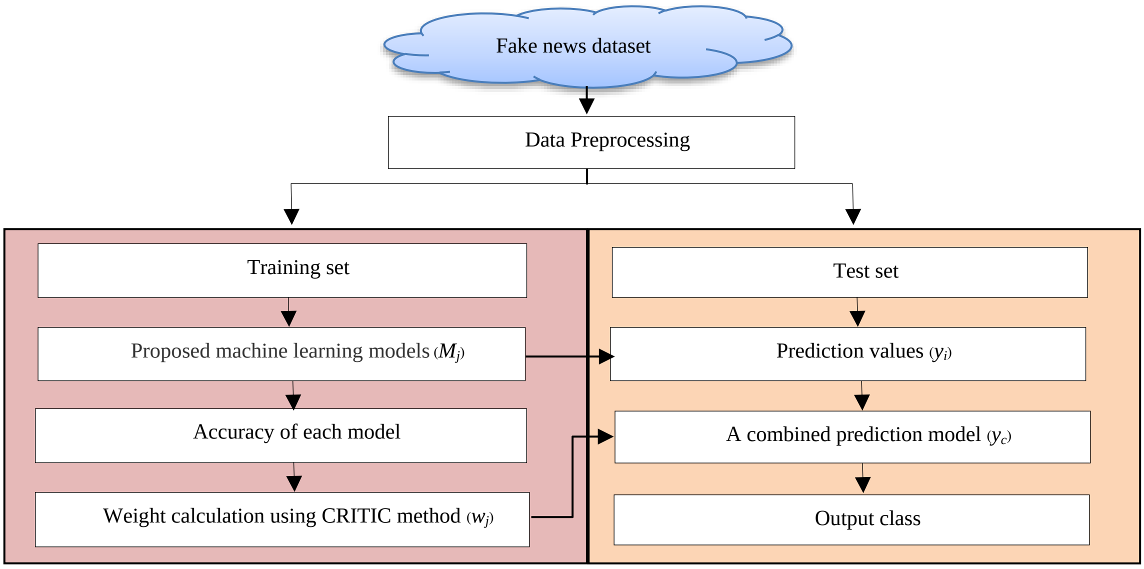

Figure 1 The framework for this paper

Table 1 Examples of the collected data

	Texts
1	คณบดีคณะแพทยศาสตร์[redacted]พยาบาล แจ้งวิธีฆ่าไวรัส covid19 ด้วยตัวเอง ฟังหมอพูดไม่ถึง 2 นาที นี้ชัดเจนมากๆครับ จะได้สบายใจ หายห่วงจากไวรัส โควิด 19 ช่วยกันแชร์เยอะๆ
2	แจ้งให้ทราบ ตึกอายุรกรรมชาย รพ.ยะลา ตอนนี้ปิดตึกเนื่องจากตรวจพบผู้ติดเชื้อโควิด-19 จำนวน 40 ราย เป็นคนไข้ 32 ราย และเจ้าหน้าที่ 8 ราย ใครมีญาติหรือคนรู้จักที่มาเยี่ยมหรือนอนที่นี่กรุณาระวังตัวด้วยน่ะคะ
3	ผีหมอไทยร่วมด้วยแล้วคะ** แพทย์ทั่วโลกเตือนภัย วัคซีนโควิด 19 ฉีดแล้วอันตรายอย่างไร ? มากกว่าที่คุณคิด!
4	แจ้งข่าวครับ มศว. ได้วัคซีน แอสตร้า มาจำนวนนึงโควต้าจากกระทรวง อว ให้เอามาฉีดนิสิต แต่นิสิตไม่มากันเพราะกลับบ้าน ตจว.เลยจะเปิดให้ ปชช. มาลงทะเบียนฉีดเลย เริ่มลงทะเบียนพรุ่งนี้ 8.30 วันนี้เข้าไปลงยังไม่ได้ ต้องพรุ่งนี้ คิวฉีดคือวันที่ 18-19-20 นี้เลย เร็วดี มหาลัยฝากมาให้ช่วยกระจายข่าว ยังไงใกล้ๆ 8.30 พรุ่งนี้ก็รีบเข้ามาดูกันครับ สถานที่ฉีดคือ [redacted] ตึก[redacted] อาจารย์หมด Chai Kusuma ฝากประชาสัมพันธ์ครับ https://vaccine.swu.ac.th/?fbclid=lwAR2PAfNeTamMUrAw6QUoCPVI_nsuigLSsOtSnaBbRnzzp6CNgP9-LmhU0ho
5	พรุ่งนี้ใครได้ฉีด AZ ล็อต CTMAV509 แปลว่าคุณได้รับวัคซีนหมดอายุเข้าสู่ร่างกาย

Note: [redacted] are the protected words.

The data is labeled into four categories: fake news, distorted news, public relations news, and true news. For this research, the data was reorganized into two classes: fake news and true news. The fake news class comprises the collected fake and distorted news data, while the true news class is composed of the collected true news and public relations news data. Following the data collection, the information was systematically organized and stored in an Excel file, facilitating subsequent data processing and analysis. This rigorous data collection and organization methodology ensures the robustness and reliability of the research findings. A Sample of the collected data is shown in Table 1.

The data utilized in this experiment is inherently unstructured, hence it cannot be directly subjected to analysis. Consequently, it is imperative to process the data, a procedure that encompasses tokenization, feature extraction, and data representation. We applied language-specific techniques to address challenges unique to Thai text, such as the absence of word spacing and complex script; therefore, the tokenization is utilized. Tokenization dissects each word in the document by its dictionary definition. Subsequently, the data is transitioned to the feature extraction process, where unique characters, previously separated by the tokenization step, are identified. Upon the identification of unique words, they are organized into a feature vector, where the sequence is not of significance. Each word in every document is then cross-referenced with the words in the feature vector. If a match is identified, it is substituted with a weight value, and if not, it is substituted with 0. This is done by the row order of the word in the document and the column of the feature word. The data is transmuted into a matrix, which is structured and primed for analysis. Google colab tool (https://colab.research.google.com), a software designed for data analysis, is employed in this research experiment, and Python version 3.0.5 is utilized for data preparation and analysis.

In terms of tokenization, this research incorporates data from fake news and true news and subjects it to the tokenization phase. This is done using the Longest Matching technique for Thai language tokenization, employing the Pythainlp library (https://pythainlp.github.io), word tokenize, Tokenizer class, and setting the engine to “longest”. The dictionary used for tokenization comprises 62,056 words. Upon completion of this phase, the fake news and true news in each document are partitioned into individual words, by the longest word identified in the dictionary, as depicted in Table 2. The text that has been tokenized by the Longest Matching technique is then ready for further analysis. Then, the words from each document obtained from the tokenization step are used to extract features using the Bag of Words technique with the Count Vectorizer class. This results in a set of unique words, numbers, and special symbols that serve as a set of features. From the feature extraction experiment, there are 6,278 features. These features are arranged in the form of a vector, also known as a feature vector, as shown in Table 2. The result obtained from feature extraction using the Bag of Word technique.

In the process of data substitution, each term derived from the document through the process of tokenization is cross-referenced with the feature vector. The corresponding weight of the term is then used as a substitute. In instances where the term is either not found or does not align with the feature, a zero is used as a placeholder. This is done by the sequential order of the term within the document and the corresponding column of the feature term. This process effectively transforms the data into a matrix format. The data substitution process employs two distinct methodologies, namely, Binary Term Frequency and Term Frequency-Inverse Document Frequency (TF-IDF).

3.2 Model training and validation for the machine learning models

The three machine learning models used in this research are Naive Bayes (NB), Decision Trees (DT) and K-Nearest Neighbors (K-NN). Each model is tested for fake news detection using the same training dataset, and each model undergoes 15 runs of validating. The validation results are then used to calculate the importance weights of each model using the CRITIC method, as demonstrated in the subsequent section.

Table 2 Text processed by the longest matching technique

	Texts
1	'คณบดี', 'คณะ', 'แพทยศาสตร์', '[redacted]', 'พยาบาล', 'แจ้ง', 'วิธี', 'ฆ่า', 'ไวรัส', 'covid19', 'ด้วยตัวเอง', 'ฟัง', 'หมอ', 'พูด', 'ไม่', 'ถึง', '2', 'นาที', 'นี่', 'ชัดเจน', 'มากๆ', 'ครับ', 'จะ', 'ได้', 'สบายใจ', 'หายห่วง', 'จาก', 'ไวรัส', 'โควิด', '19', 'ช่วยกัน', 'แชร์', 'เย', 'อะๆ'
2	'แจ้งให้ทราบ', 'ตึก', 'อายุรกรรม', 'ชาย', 'รพ.', 'ยะลา', 'ตอนนี้', 'ปิด', 'ตึก', 'เนื่องจาก', 'ตรวจ', 'พบ', 'ผู้', 'ติดเชื้อ', 'โค', 'วิด', '-', '19', 'จำนวน', '40', 'ราย', 'เป็น', 'คนไข้', '32', 'ราย', 'และ', 'เจ้าหน้าที่', '8', 'ราย', 'ใคร', 'มี', 'ญาติ', 'หรือ', 'คนรู้จัก', 'ที่มา', 'เยี่ยม', 'หรือ', 'นอน', 'ที่นี่', 'กรุณา', 'ระวังตัว', 'ด้วย', 'น่ะ', 'ค๊ะ'
3	'ผี', 'หมอไทย', 'ร่วม', 'ด้วย', 'แล้ว', 'คะ', '**', 'แพทย์', 'ทั่วโลก', 'เตือนภัย', 'วัคซีน', 'โควิด', '19', 'ฉีด', 'แล้ว', 'อันตราย', 'อย่าง', 'ไร', '?', 'มากกว่า', 'ที่', 'คุณ', 'คิด', '!'
4	'แจ้ง', 'ข่าว', 'ครับ', 'มศว.', 'ได้', 'วัคซีน', 'แอ', 'สต', 'ร้า', 'มา', 'จำนวน', 'นึง', 'โควต้า', 'จาก', 'กระ', 'ทร', 'วง', 'อว', 'ให้', 'เอา', 'มา', 'ฉีด', 'นิสิต', 'แต่', 'นิสิต', 'ไม่', 'มา', 'กัน', 'เพราะ', 'กลับบ้าน', 'ตจ', 'ว.', 'เลย', 'จะ', 'เปิด', 'ให้', 'ปชช.', 'มา', 'ลงทะเบียน', 'ฉีด', 'เลย', 'เริ่ม', 'ลงทะเบียน', 'พรุ่งนี้', '8', '.', '30', 'วันนี้', 'เข้าไป', 'ลง', 'ยัง', 'ไม่', 'ได้', 'ต้อง', 'พรุ่งนี้', 'คิว', 'ฉีด', 'คือ', 'วันที่', '18', '-', '19', '-', '20', 'นี้', 'เลย', 'เร็ว', 'ดี', 'มหาลัย', 'ฝาก', 'มา', 'ให้', 'ช่วย', 'กระจาย', 'ข่าว', 'ยังไง', 'ใกล้ๆ', '8', '.', '30', 'พรุ่งนี้', 'ก็', 'รีย', 'เข้ามา', 'ดู', 'กัน', 'ครับ', 'สถานที่', 'ฉีด', 'คือ', '[redacted]', '[redacted]', '[redacted]', 'ตึก', '[redacted]', 'อาจารย์', 'หมด', 'chai', 'kusuma', 'ฝาก', 'ประชาสัมพันธ์', 'ครับ', 'https', '://', 'vaccine', '.', 'swu', '.', 'ac', '.', 'th', '/?','fbclid','=','lwar2pafnetammuraw6quocpvi','_', 'nsuiglssotsnabbrnzzp6cngp9', '-', 'lmhu0ho'
5	'พรุ่งนี้', 'ใคร', 'ได้', 'ฉีด', 'az', 'ล็อต', 'ctmav509', 'แปล', 'ว่า', 'คุณ', 'ได้รับ', 'วัคซีน', 'หมดอายุ', 'เข้าสู่', 'ร่างกาย'

Note: [redacted]. are the protected words.

3.3 Implementation of the CRITIC method to generate criteria weights for each model

Alinezhad, and Khalili (2019) described that the CRITIC method (Criteria Importance Through Intercriteria Correlation) represents a method focused on correlation analysis. This approach utilizes standard deviations of ranked criteria values of various options presented in columns, along with correlation coefficients of all possible pairs of columns. These measures are instrumental in determining the contrast among different criteria.

Step 1 entails creating the generalized decision matrix (E), as illustrated in Equation (1).

$$E = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix}_{mxn} \end{array} \tag{1}$$

Step 2 involves normalizing the elements within the generalized decision matrix. This process is applied to the decision matrix (X), which is detailed in Equation (2).

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \xi_{11} & \xi_{12} & \cdots & \xi_{1n} \\ \xi_{21} & \xi_{22} & \cdots & \xi_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \xi_{m1} & \xi_{m2} & \cdots & \xi_{mn} \end{bmatrix}_{mxn} \end{array} \tag{2}$$

The normalization of matrix elements $X = [\xi_{ii}]_{mxn}$ is done by applying (3) and (4).

a) for maximizing criteria:

$$\xi_{ij} = \frac{\xi_{ij} - \xi_j^{\min}}{\xi_j^{\max} - \xi_j^{\min}},\ i = 1, 2, ..., n;\ \ j = 1, 2, ..., m \tag{3}$$

b) for minimizing criteria

$$\xi_{ij} = \frac{\xi_j^{\max} - \xi_{ij}}{\xi_j^{\max} - \xi_j^{\min}},\ i=1,2,...,n;\ \ j=1,2,...,m. \qquad (4)$$

where $\xi_j^{\max} = \max_j \left\{\xi_{1j}, \xi_{2j}, ..., \xi_{mj}\right\}$;

$\xi_j^{\min} = \min_j \left\{\xi_{1j}, \xi_{2j}, ..., \xi_{mj}\right\}$.

After the normalization process is applied to the criteria in the initial decision matrix, each element ξ_{1j} is scaled down to the range [0, 1]. This scaling ensures that all criteria are measured using a uniform metric.

Step 3 involves determining the standard deviation, denoted as σ_j, for the criterion $C_i(j=1,2,...,n)$. This standard deviation signifies the extent of variation in the values of alternatives for the specified criterion from the average value. In subsequent stages, this measure of standard deviation for each criterion is utilized as a key factor in establishing the weight coefficients for the criteria.

In Step 4, from the normalized matrix $X=[\xi_{ij}]_{mxn}$, we extract the vector $\xi_j = \left\{\xi_{1j}, \xi_{2j}, ..., \xi_{mj}\right\}$, which encapsulates the values of alternatives $A_i(i=1,2,..,m)$ corresponding to the specific criterion $C_i(j=1,2,...,n)$. Following the creation of the vector $\xi_j = \left\{\xi_{1j}, \xi_{2j}, ..., \xi_{mj}\right\}$, we proceed to formulate the matrix $L=[l_{jk}]_{mxn}$. This matrix comprises coefficients representing the linear correlation between vectors ξ_j and ξ_k. The principle here is that a greater divergence in the criteria values of options for criteria *j* and *k* corresponds to a reduced value of the coefficient l_{jk}. Consequently, expression (5) is indicative of the degree of conflict of criterion j relative to other criteria within the specified decision matrix.

$$\varphi_j = \sum_{k=1}^{n}(1-l_{jk}) \qquad (5)$$

The quantity of data C_j contained within criterion *j* is determined by combining previously listed measures σ_j and l_{jk}, as shown in Equation (6).

$$C_j = \sigma_j \cdot \varphi_j = \sigma_j \sum_{k=1}^{n}(1-l_{kj}) \qquad (6)$$

The analysis conducted previously leads to the conclusion that a higher value of C_j signifies a larger amount of data derived from a certain criterion. This increased data volume subsequently enhances the relative importance of this criterion in the context of the decision-making process.

In Step 5, the objective weights of the criteria, denoted as w_j and presented in Equation (7), are obtained by normalizing the measures C_j.

$$w_j = C_j \Big/ \sum_{k=1}^{m} C_k \qquad (7)$$

3.4 Testing the proposed model

The combined prediction model ($\hat{y}_c$), Equation (8), is obtained by multiplying the weight value of each model (w_j) by the corresponding prediction of each machine learning model (y_j).

$$\hat{y}_c = \sum_{j=1}^{n} w_j \cdot y_j \qquad (8)$$

If $\hat{y}_c \geq 0.5$, classify it as Class 1. If $\hat{y}_c < 0.5$, classify as Class 0.

4. Results

This research introduces a hybrid method utilizing the CRITIC method and the well-known machine learning models (Naive Bayes, Decision Tree, and K-Nearest Neighbors) for the detection of fake news in Thai language. The detailed approach is as follows:

4.1 Model training and validation for the machine learning model

The objective of this study was to develop novel models derived from three established machine learning algorithms, namely, Naïve Bayes (M_1), Decision Tree (M_2), and K-Nearest Neighbors (M_3). Each model underwent a validation process over 15 epochs. The validation accuracy of each conventional model, when applied to the Thai Fake News dataset, was recorded for each epoch during the training process. This data was utilized to evaluate the performance of the ensemble models.

The box plot comparing training accuracy is shown in Figure 2.

As seen in Figure 2, M_3 exhibits the highest mean accuracy, with a minimum value of 81.79% and a maximum value of 86.99%. Conversely, M_2 demonstrates the lowest mean accuracy, possessing a minimum value of 76.87% and a maximum value of 84.97%.

4.2 Implementation of the CRITIC method to generate criteria weights for each model

Upon acquiring the validation accuracy for each model, these accuracy values were employed to generate the generalized decision matrix. The generalized decision matrix was shown in Table 3.

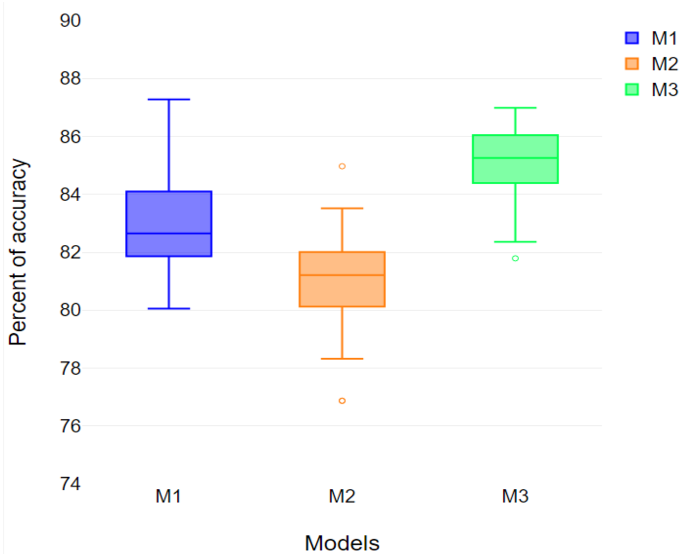

Figure 2 Box plot of the comparison training accuracy

Table 3 Generalized decision matrix

Run	M_1	M_2	M_3
1	87.28	76.87	85.26
2	83.52	81.50	84.97
3	81.21	80.34	84.39
4	82.65	81.79	84.39
5	84.39	83.52	85.26
6	81.50	81.21	84.39
7	82.65	82.08	85.83
8	84.10	84.97	86.41
9	84.10	80.34	86.99
10	80.05	80.05	82.36
11	82.65	78.32	84.39
12	82.08	81.79	86.12
13	81.79	80.92	81.79
14	84.10	83.52	86.41
15	82.94	76.87	85.83
min	**80.05**	**76.87**	**81.79**
max	**87.28**	**84.97**	**86.99**

Table 4 Normalized decision matrix

Run	M_1	M_2	M_3
1	1.0000	0.0000	0.6673
2	0.4799	0.5716	0.6115
3	0.1604	0.4284	0.5000
4	0.3596	0.6074	0.5000
5	0.6003	0.8210	0.6673
6	0.2006	0.5358	0.5000
7	0.3596	0.6432	0.7769
8	0.5602	1.0000	0.8885
9	0.5602	0.4284	1.0000
10	0.0000	0.3926	0.1096
11	0.3596	0.1790	0.5000
12	0.2808	0.6074	0.8327
13	0.2407	0.5000	0.0000
14	0.5602	0.8210	0.8885
15	0.3997	0.0000	0.7769
σ_j	**0.2367**	**0.2842**	**0.2790**

Table 5 Linear correlation matrix

	M_1	M_2	M_3
M_1	1.0000	-0.0713	0.5607
M_2	-0.0713	1.0000	0.2125
M_3	0.5607	0.2125	1.0000

Table 6 The weights for each criterion

	M_1	M_2	M_3
M_1	0.000	1.071	0.439
M_2	1.071	0.000	0.787
M_3	0.439	0.787	0.000
sum(1-r)	1.5106	1.8587	1.2268
C_j	0.3575	0.5283	0.3423
w_j	0.2911	0.4302	0.2787

Table 7 The performance of each model

Model	Accuracy
Naïve Bayes (M1)	80.83
Decision Tree (M2)	80.37
K-Nearest Neighbors (M3)	75.75
Our Proposed	83.37

After obtaining the generalized decision matrix, the normalized decision matrix was generated using Equations (2) to (4). As a result,the normalized decision matrix was shown in Table 4. After obtaining the normalized decision matrix, the linear correlation matrix was generated using Equation (5). As a result,the linear correlation matrix was shown in Table 5. After obtaining the linear correlation matrix, the quantity of data (C_j) was generated using Equation (6). After that, the criteria weights was obtained using Equation (7). As a result, the weights for each criterion were shown in Table 6.

4.3 Testing the proposed model

The proposed prediction model, using Equation (8), was tested with the testing set. The performances of the proposed model and other models on the Thai Fake News dataset are shown in Table 7.

The experimental results presented in Table 7 reveal that the accuracy of the proposed method is 83.37%, which is higher than that of Naive Bayes

(80.83%), Decision Tree (80.37%), and K-Nearest Neighbors (75.75%). This finding demonstrates a substantial improvement in performance, as the suggested approach achieves a 7.62% advantage over the established models. Thus, the proposed integrated approach can be implemented as a remedy for text mining and related issues.

The proposed method outperforms individual models in terms of accuracy. This is because the proposed method assigns greater weight to more effective models, unlike the average weight method, which assigns equal weight to all models. The proposed method employs the CRITIC method, a widely accepted objective weighting method in multi-criteria decision making, to calculate the weight of each model. The literature review reveals that there is only one research study related to detecting fake news in the Thai language, specifically the work of Chumnankit, & Siriborvornratanakul (2022). They introduced a method for detecting fake news in the Thai language using natural language processing techniques. This method involved the classification of headlines pre-filtered by the Anti-Fake News Center Thailand, focusing on health product-related news, encompassing a total of 339 headlines for classification. The approach entailed comparing words or phrases consistent with fake news to determine the class. Their experimental results demonstrated an overall accuracy rate of 80.00% for headline classification and an improved rate of 84.17% when focusing specifically on nouns and classifiers. Despite the presented method having an efficiency of 83.37%, which is slightly lower than that of Chumnankit, & Siriborvornratanakul (2022), it lacked the feature selection step. Feature selection is a critical phase in data preprocessing that enhances the efficiency and effectiveness of a machine learning model. Therefore, it is believed that the incorporation of feature selection into the presented method could potentially enhance its performance.

5. Conclusions

In the digital era, the escalating prevalence of false news, particularly on social media platforms, has emerged as a significant threat to the credibility of public discourse. Combining the CRITIC method with numerous machine learning models, this paper introduces a novel hybrid approach for detecting fake news in the Thai language. The first stage involves accumulating information from websites about Thai-language fake news. The data is then subjected to a preprocessing phase. In the second stage, preprocessed data is validated using three fundamental machine learning models: Naive Bayes, Decision Tree, and K-Nearest Neighbors. In the third phase, the accuracy findings from these three models are used to determine the significance weights for each model using the CRITIC method. Using the proposed procedure, predictions are recalculated in the final stage. According to experimental findings, the introduced procedure improves the efficacy of all three original models. Specifically, the proposed accuracy of the Naive Bayes, Decision Tree, and K-Nearest Neighbors models is 83.37 percent, 80.83 percent, 80.37 percent, and 75.75 percent, respectively. The proposed hybrid approach showcases the effectiveness of ensemble learning in improving the accuracy and efficiency of fake news detection, contributing significantly to the field and promoting a more reliable information ecosystem. As a consequence of this, the technique that has been suggested has the potential to improve the performance of fake news identification in the Thai language by making use of an ensemble of the original models. The fact that this method is so straightforward while still producing excellent results is one of its primary selling points.

The implementation of this method in a variety of languages and areas might be investigated in further study, as could the investigation into the inclusion of additional linguistic and contextual characteristics in order to improve detection capabilities. In addition, it would be helpful to generate datasets that are more extensive and are geared specifically toward the Thai language.

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7. References

Ahmad, U., Khan, A., & Saeid, A. B. (2023). Integrated multi-criteria group decision-making methods based on q-rung picture fuzzy sets for the identification of occupational hazards. *Soft Computing*, 2023, 1–24. https://doi.org/10.1007/s00500-023-08154-4

Al-shami, T. M., & Mhemdi, A. (2023). Generalized frame for orthopair fuzzy sets:(m, n)-fuzzy sets and their applications to multi-criteria decision-making methods. *Information*, *14*(1), Article 56. https://doi.org/10.3390/info14010056

Alghamdi, J., Lin, Y., & Luo, S. (2022). A Comparative Study of Machine Learning and Deep Learning Techniques for Fake News Detection. *Information*, *13*, Article 576. https://doi.org/10.3390/info13120576

Alghamdi, J., Lin, Y., & Luo, S. (2023). Does Context Matter? Effective Deep Learning Approaches to Curb Fake News Dissemination on Social Media. *Applied Sciences*, *13*(5), Article 3345.

Alinezhad, A., & Khalili, J. (2019). *New Methods and Applications in Multiple Attribute Decision Making (MADM)*. Springer. 10.1007/978-3-030-15009-9

Allcott, H., & Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, *31*(2), 211–236. https://doi.org/10.1257/jep.31.2.211

Chen, C.-T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, *114*(1), 1–9. https://doi.org/10.1016/S0165-0114(97)00377-1

Chumnankit, T. & Siriborvornratanakul, T. (2022). Thai Fake News Detection Using Natural Language Processing. *KMUTT Research & Development Journal*, *45*(2), 275-287. https://doi.org/10.14456/kmuttrd.2022.16

Gururaj, H. L., Lakshmi, H., Soundarya, B. C., Flammini, F., & Janhavi, V. (2022). Machine Learning-Based Approach for Fake News Detection. *Journal of ICT Standardization*, *10*(4), 509–530. https://doi.org/10.13052/jicts 2245-800X.1042

Jlifi, B., Sakrani, C., & Duvallet, C. (2022). Towards a soft three-level voting model (Soft T-LVM) for fake news detection. *Journal of Intelligent Information Systems*, *61*(1), 249-269. https://doi.org/10.1007/s10844-022-00769-7

Khanmohammadi, S., & Rezaei, N. (2021). Role of Toll-like receptors in the pathogenesis of COVID-19. *Journal of Medical Virology, 93*(5), 2735–2739. https://doi.org/10.1002/jmv.26826

Kongwan, A., Kamaruddin, S. S., & Ahmad, F. K. (2022). Anaphora resolution in Thai EDU segmentation. *Journal of Computer Science, 18*, 306-315. https://doi.org/10.3844/jcssp.2022.306.315

Lai, Y.-J., Liu, T.-Y., & Hwang, C.-L. (1994). Topsis for MODM. *European Journal of Operational Research*, *76*(3), 486–500. https://doi.org/10.1016/0377-2217(94)90282-8

Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., … Rothschild, D. (2018). The science of fake news. *Science*, *359*(6380), 1094–1096. https://doi.org/10.1126/science.aao2998

Liu, Y., & Wu, Y.-F. (2018). Early detection of fake news on social media through propagation path classification with recurrent and convolutional networks. In *Proceedings of the AAAI conference on artificial intelligence 32*(1). https://doi.org/10.1609/aaai.v32i1. 11268

Murugesan, S., & Pachamuthu, K. (2022). Fake News Detection in the Medical Field Using Machine Learning Techniques. *International Journal of Safety & Security Engineering*, *12*(6), 723-727. https://doi.org/10.18280/ijsse.120608

Nasawat, P., Talangkun, S., Arunyanart, S., & Wichapa, N. (2021). Hybrid cross-efficiency approach based on ideal and anti-ideal points and the critic method for ranking decision-making units: a case study on ranking the methods of rice weevil disinfestation. *Decision Science Letters*, *10*(3), 375–392.

Opricovic, S., & Tzeng, G.-H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, *156*(2), 445–455. https://doi.org/10.1016/S0377-2217(03)00020-1

Pandey, S., Prabhakaran, P., Reddy, N. V. S., & Acharya, D. (2022). Fake News Detection from Online media using Machine Learning Classifiers. Journal of Physics: Conference Series. *2161*, 1-12. https://doi.org/10.1088/1742-6596/2161/1/012027

Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake news detection on social media: A data mining perspective. *ACM SIGKDD Explorations Newsletter*, *19*(1), 22–36. https://doi.org/10.1145/3137597.3137600

Tzeng, G.-H., & Huang, J.-J. (2011). *Multiple attribute decision making: methods and applications*. CRC press.

Wang, H., Dou, Y., Chen, C., Sun, L., Yu, P. S., & Shu, K. (2023). Attacking Fake News Detectors via Manipulating News Social Engagement. *ArXiv Preprint ArXiv:2302.07363*. https://doi.org/10.48550/arXiv.2302.07363

Wang, T.-C., & Lee, H.-D. (2009). Developing a fuzzy TOPSIS approach based on subjective weights and objective weights. *Expert Systems with Applications*, *36*(5), 8980–8985. https://doi.org/10.1016/j.eswa.2008.11.035

Wichapa, N., Khokhajaikiat, P., & Chaiphet, K. (2021). Aggregating the results of benevolent and aggressive models by the CRITIC method for ranking of decision-making units: A case study on seven biomass fuel briquettes generated from agricultural waste. *Decision Science Letters*, *10*(1), 79–92. https://doi.org/10.5267/j.dsl.2020.10.001

Xu, L., & Yang, J.-B. (2001). *Introduction to multi-criteria decision making and the evidential reasoning approach* (Vol. 106). Manchester School of Management Manchester. https://personalpages.manchester.ac.uk/staff/jian-bo.yang/JB%20Yang%20Book_Chapters/XuYang_MSM_WorkingPaperFinal.pdf

Zampieri, M., Malmasi, S., Nakov, P., Rosenthal, S., Farra, N., & Kumar, R. (2019). Semeval-2019 task 6: Identifying and categorizing offensive language in social media (offenseval). *ArXiv Preprint ArXiv:1903.08983*. https://doi.org/10.18653/v1/S19-2010

Zeleny, M. (2012). *Multiple criteria decision making Kyoto 1975* (Vol. 123). Springer Science & Business Media.

Zhou, X., & Zafarani, R. (2018). Fake news: A survey of research, detection methods, and opportunities. *ArXiv Preprint ArXiv:1812.00315*, 2. https://doi.org/10.48550/arXiv.1812.00315