 ISSN 2579-7298

Comparative Study of Fuzzy Inference System and Adaptive Neuro-Fuzzy Inference System in Public Sentiment Analysis of Kabinet Merah Putih

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ARTICLE INFO

Article history
Received 18 Juni 2025
Revised 23 August 2025
Accepted 10 Okt 2025

Keywords
Adaptive Neuro-Fuzzy Inference System, Fuzzy Inference System, Sentiment Analysis, Social Media, Kabinet Merah Putih, Public Opinion

ABSTRACT

This study aims to compare two fuzzy logic-based approaches, namely the Fuzzy Inference System (FIS) and the Adaptive Neuro-Fuzzy Inference System (ANFIS), in analyzing public sentiment toward the Kabinet Merah Putih. A dataset of 1,197 tweets was collected from Twitter (X) between October 2024 and April 2025 using specific keywords. After preprocessing and polarity measurement with TextBlob, the sentiment values were mapped into seven categories: strongly negative, negative, weakly negative, neutral, weakly positive, positive, and strongly positive. The classification was performed using both FIS and ANFIS. Evaluation metrics included accuracy, precision, recall, F1-score, and error rate (MSE and RMSE). Experimental results show that FIS achieved an overall accuracy of 79.2%, performing well on majority classes but failing to identify several minority classes. In contrast, ANFIS obtained an accuracy of 92.5% with very low error (MSE = 0.0341, RMSE = 0.1848), demonstrating strong capability in classifying majority and several minority categories. Overall, ANFIS outperformed FIS, proving more effective in capturing sentiment patterns and aligning with the actual distribution of public opinion. This study offers novelty by explicitly comparing the performance of FIS and ANFIS in multi-level sentiment analysis of Indonesian social media data, an approach that has not been explored in prior research.

1. Introduction

Government performance is consistently under public scrutiny and elicits various responses, both positive and negative. Citizens actively express their opinions across multiple platforms especially social media which has become an open, expressive public sphere. This development creates a need for methods capable of reading, processing, and understanding public opinion in a more systematic way [1].

Fuzzy logic has been widely used in sentiment analysis for handling uncertainty and ambiguity in natural-language data [2],[3]. It allows sentiment classification not only in extreme forms (positive/negative) but also in graded forms, thereby more realistically representing the nuances of public emotions.

This study focuses on the Kabinet Merah Putih as the analysis object because this cabinet has received broad public attention across various policy issues. Using two approaches Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy Inference System (ANFIS) [4], [5] we implement a more granular scheme by dividing sentiment into seven categories: strongly positive, positive, weakly positive, neutral, weakly negative, negative, and strongly negative, to produce a more accurate and informative mapping of public opinion.

Few studies explicitly compare the performance of these two methods on Indonesian social-media data. While fuzzy logic approaches have been used to address uncertainty and ambiguity in natural language within public opinion often using five categories comparative evidence remains limited [6]. Some prior works integrated ANFIS with other methods (e.g., SVM) to improve accuracy in political analysis. Other studies [7] classified sentiment (e.g., COVID-19) using ANFIS and achieved strong accuracy. Previous work by Budiati [8] divided sentiment into seven categories using single-input fuzzy logic without a train/test split. In this study, we compare FIS which provides flexibility via linguistic rules with ANFIS as an adaptive alternative that combines the strengths of fuzzy logic and neural networks. Furthermore, this research evaluates the performance of both methods in terms of accuracy and classification capability. The findings are expected to be useful for government agencies, social-media analysts, and policymakers as a reference for understanding public perceptions of cabinet performance

2. METHODS

The processes of data collection, data preprocessing, and polarity measurement have been carried out in several previous studies [9], [10]. Meanwhile, the fuzzy logic process using the two methods FIS and ANFIS up to the development of the evaluation model will be completed in this study.

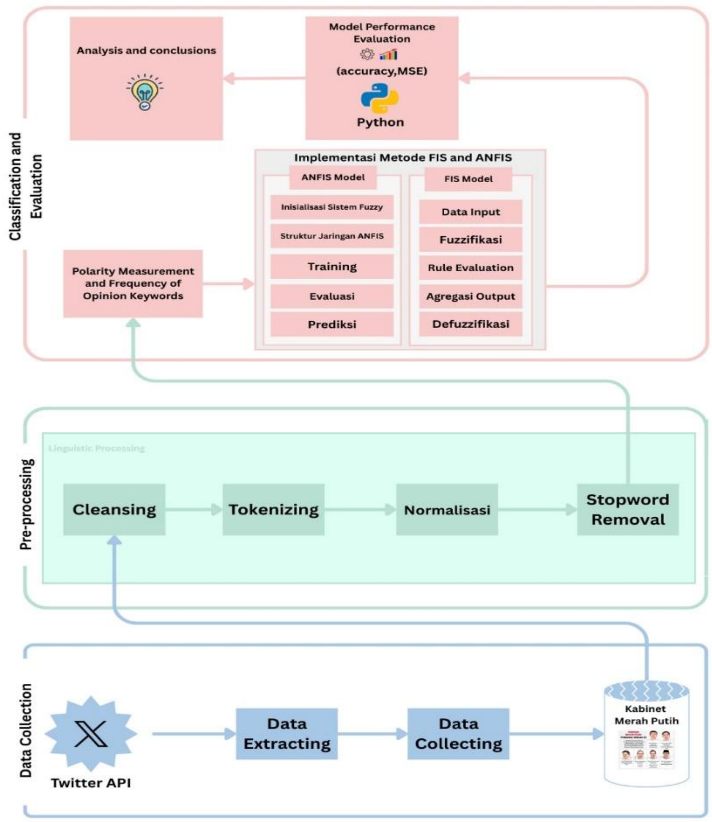

Fig. 1. Research Method Flowchart

3.1. Data Collection

Data collection was conducted using the Twitter/X API. Tweets were retrieved in JSON format containing the text and additional metadata, including username, upload time, number of likes, and retweets. Data were collected from 21 October 2024 to 29 April 2025 using the keywords “Kabinet Merah Putih” and “Kabinet Prabowo”.

3.2. Data Preprocessing

Preprocessing steps included removing stopwords, non-alphabetic characters, and normalizing letter case, as well as cleaning hashtags, mentions, and hyperlinks. The data were then translated into English using a deep translator, followed by tokenization of the texts into tokens.

Polarity Measurement

TextBlob was used to compute polarity scores in the range −1 to 1. The classification is defined as follows:

1. Positive if the polarity score > 0
2. Neutral if the polarity score = 0
3. Negative if the polarity score < 0

Fuzzy-Logic Modeling

Classification using conventional Natural Language Processing still exhibits substantial gaps, which can lead to less accurate sentiment analysis [9]. Therefore, we incorporate the frequency of opinion keywords, which is then rationalized in the fuzzy-logic stage.

Fuzzy Inference System (FIS)

A fuzzy inference system with IF THEN rules to determine sentiment categories based on extracted features. [11]

a) Apply all IF THEN rules based on membership degrees.
b) Aggregate outputs using max or sum operators.
c) Defuzzify via the centroid method to obtain the final numerical output.
d) Interpret that output into seven sentiment categories.

General triangular membership function:

$$\boxed{\mu[x,a,b,c] = \{\, \mu[x,a,b,c] = \begin{cases} 0\,; & x \le a \;or\; x \ge c \\ \frac{x-a}{b-a}; & if\; a \le x \le b \\ \frac{c-x}{c-b}; & if\; b \le x \le c \end{cases}} \tag{1}$$

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Introduced by Jang [12], ANFIS integrates artificial neural networks and fuzzy logic to learn sentiment patterns from preprocessed data. Architecture includes: [12]–[16]

1. Input Layer
2. Fuzzy system initialization

   ANFIS consists of five layers:

   a. Input MF, calculates the degree of membership using a sigmoid function.
   b. Rule Layer: firing strength is calculated as the product of each pair of input values.
   c. Normalization, firing strength is divided by the total firing strength
   d. The consequent layer is formulated with rules:

   $$\boxed{z = p_1.X_1 + p_2.X_2 + \cdots + p_n.X_n + r} \tag{2}$$

   a. Final output from all rules:

   $$\boxed{Output = \textstyle\sum_{i=1}^{N} \bar{w}_i \,.\, z_i} \tag{3}$$

   The final output is represented as a score within a range, which is then classified into seven categories.
3. The training process is carried out using the dataset (input and target output).
4. Evaluation, measured through Mean Squared Error (MSE), accuracy, and the confusion matrix

$$\boxed{MSE = \frac{1}{n}\sum\nolimits_{1}^{n}(y_i - \hat{y})^2} \quad (4)$$

$$\boxed{Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Correct\ Predictions}\ x\ 100\%} \quad (5)$$

5. Prediction: Once training is completed, new data (input 1 and input 2) are provided to the system. ANFIS processes the inputs through its five layer architecture and generates an output corresponding to a specific sentiment category

The layers of ANFIS are illustrated in Figure 2

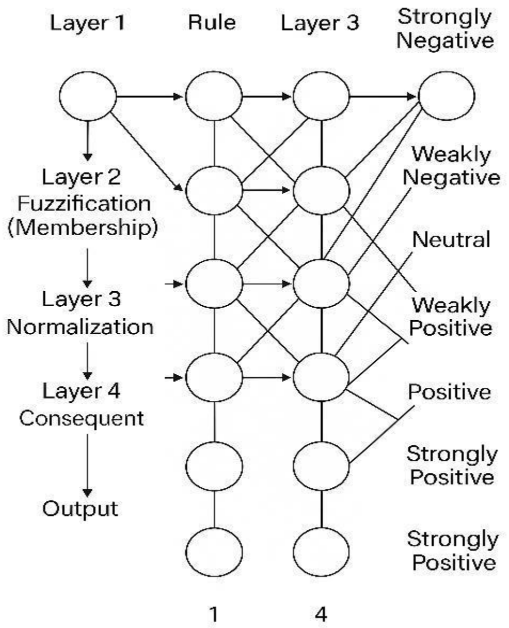

Fig. 2.ANFIS Architecture

3. RESULT AND DISCUSSION

The collected Twitter data are visualized in a word cloud where font size represents word frequency.

Fig 3 Word Cloud

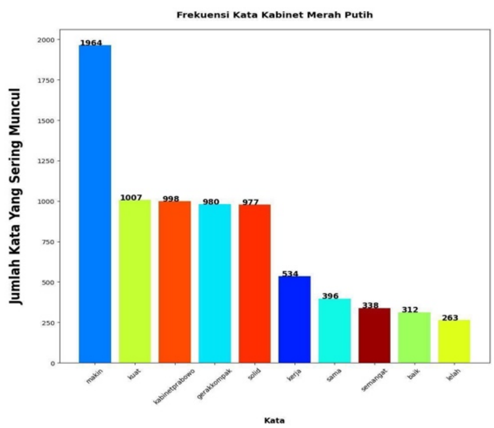

Fig 4 Frequency of Word Occurrence

The frequency chart in Figure 4 reinforces the results of the word cloud, indicating that public opinion regarding the Kabinet Merah Putih is dominated by positive-toned words such as *makin* (increasingly), *kuat* (strong), *solid*, *kompak* (united), *kerja* (work), *semangat* (spirit), and *baik* (good). Based on polarity, sentiment values categorized into positive, neutral, and negative are shown below:

	stemming_data	english_kabinet	sentimen_kabinet	polaritas
0	menkes budi soal isu reshuffle wah hak beliau ...	Minister of Health Budi about the issue of res...	Positif	0.100000
1	muzani sebut ada informasi resmi soal reshuffl...	Muzani said that there was official informatio...	Netral	0.000000
2	hensat ingat suka gaduh perintah kalau gaduh t...	Hensat remembers like a rowing order when nois...	Netral	0.000000
3	tiga menteri nilai jadi beban kabinet amat des...	Three Ministers of Value So the burden of the ...	Positif	0.150000
4	presiden prabowo tunjuk bimo wijayanto jadi di...	President Prabowo appointed Bimo Wijayanto to ...	Positif	0.050000
...	...	...	...	...
1192	teman yakin yakin mampu sama gerakkompak kabin...	Friends believe that they are able to be the s...	Positif	0.250000
1193	lets go teman semangat sama gerakkompak kabine...	Let's Go Friend Spirit with Compact Motion Cab...	Positif	0.477778
1194	tuju banget bangsa hak dapat baik gerakkompak ...	really aimed at the rights nation to be good c...	Positif	0.320000
1195	lets go fren semangat bareng gerakkompak kabin...	Let's Go Green Spirit Together with the Prabow...	Positif	0.100000
1196	bener sekali semangat gerakkompak kabinetprabo...	It is true that the spirit of compact movement...	Positif	0.092857

1197 rows × 4 columns

Fig 5 Polarity Score Distribution

Based on the chart in Figure 5, it can be observed that positive sentiment accounts for 913 instances (76.21%), neutral sentiment for 203 instances (16.96%), and negative sentiment for 81 instances (6.77%). FIS classification into seven categories is presented below.

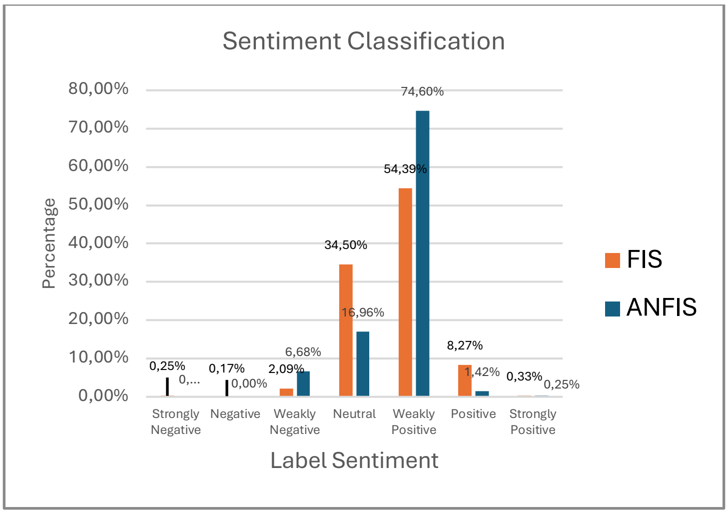

Fig 6 Sentiment Classification into Seven Categories FIS and ANFIS

In FIS, Weakly Positive dominated (54.39%), followed by Positive (8.27%) and Strongly Positive (0.33%), while Neutral sentiment rose from 37.99% to 57.20% after applying fuzzy logic. In ANFIS, public opinion was mainly Weakly Positive (74.6%), followed by Neutral (16.96%).

Table 1. Sentiment Category Analysis Results (FIS)

Sentiment	Precision	Recall	F1-score	Support
Negative	0.000	0.000	0.000	1
Neutral	0.701	0.832	0.761	123
Positive	0.752	0.451	0.564	20
Strongly Negative	0.000	0.000	0.000	2
Strongly Positive	0.000	0.000	0.000	2
Weakly Negative	1.000	0.121	0.225	8
Weakly Positive	0.862	0.852	0.852	204
accuracy	0.792	0.792	0.792	360
macro avg	0.473	0.322	0.346	360

Weighted avg	0.792	0.792	0.782	360

The testing results showed an overall accuracy of 79.2%, indicating that FIS is generally capable of classification with reasonable accuracy. The Neutral and Weakly Positive categories, as the majority classes, achieved the best outcomes with F1-scores of 0.761 and 0.852. The Positive sentiment was only partially recognized (F1 = 0.564), reflecting substantial misclassification, while the Negative, Strongly Negative, and Strongly Positive categories were almost entirely unrecognized, with recall values of 0.000.

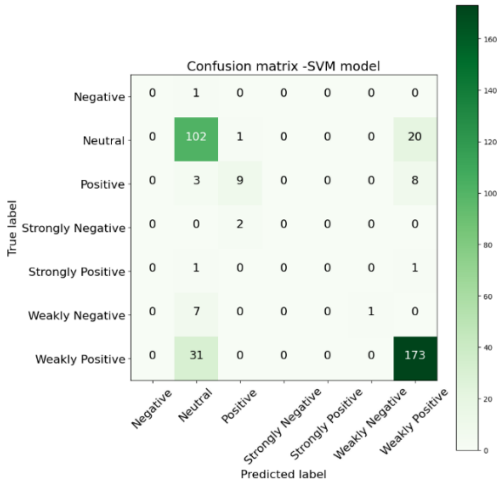

Fig 7 Confusion Matrix-FIS

The results of the confusion matrix indicate that the model performs reasonably well in recognizing the majority categories; however, it still encounters difficulties in classifying the minority categories. Overall, this distribution pattern is consistent with the distribution of public sentiment, which is predominantly dominated by the Weakly Positive (54.39%) and Neutral (34.50%) categories In ANFIS, the dataset was proportionally divided with a ratio of 70% (838 data points) for training and 30% (359 data points) for testing. The training data were used to train the ANFIS model to recognize sentiment patterns, while the testing data were employed to evaluate the model's performance on unseen data. This proportional division enables objective evaluation [17], [18]. The testing results reflect the model's accuracy in predicting new data.

Epoch

An epoch is defined as one complete training cycle in which the entire training dataset is fed into the model to adjust its parameters . In each epoch, the model learns data patterns, computes the error, and subsequently updates its parameters in order to minimize the error.

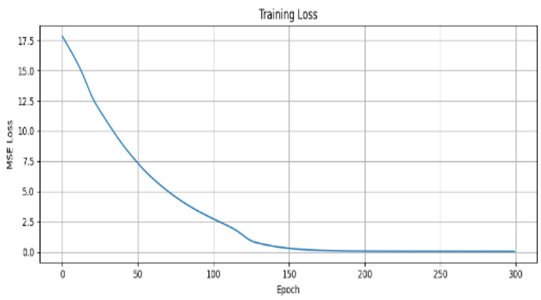

Fig 8 Training Loss Curve

Figure 8 illustrates the change in MSE loss during the training process over 300 epochs. The initial loss was relatively high, approximately 17.8, but a significant decrease was observed within the first 50 epochs. Between epochs 50 and 150, the decline became more stable and consistent, approaching a value of around 0.5, indicating that the model was increasingly able to recognize data patterns effectively. By the end of training, the loss value was very close to zero and remained stable, suggesting that the model had reached convergence and that additional epochs would no longer provide significant improvements.

Based on the testing results, the performance of the ANFIS model is demonstrated by the values of precision, recall, and F1-score for each sentiment category.

Table 2. Results of ANFIS Model Evaluation

Sentiment	Precision	Recall	F1-Score	Support
Negative	0.000	0.000	0.000	0
Neutral	0.000	0.000	0.000	0
Positive	0.000	0.000	0.000	26
Strongly Negative	1.000	0.984	0.992	61
Strongly Positive	0.996	1.000	0.998	264
Weakly Negative	1.000	1.000	1.000	8
Weakly Positive	1.000	1.000	1.000	1
Accuracy	0.925	0.925	0.925	360
Macro avg	0.666	0.664	.0665	360
Weighted avg	0.925	0.925	0.925	360

The model achieved an accuracy of 92.5%, indicating that the majority of predictions corresponded to the actual targets. The Strongly Positive category demonstrated the best performance, with a recall of 1.000 and an F1-score of 0.998, meaning that the model was able to correctly identify nearly all instances. The Strongly Negative category also exhibited high performance, while the Weakly Negative category achieved perfect performance with precision, recall, and F1-score all equal to 1.000. Conversely, the Positive sentiment class was not recognized by the model (precision and recall = 0.000), which can be attributed to the imbalanced data distribution that biased the model toward categories with larger sample sizes. The Weakly Positive class contained only one instance, which was correctly predicted.

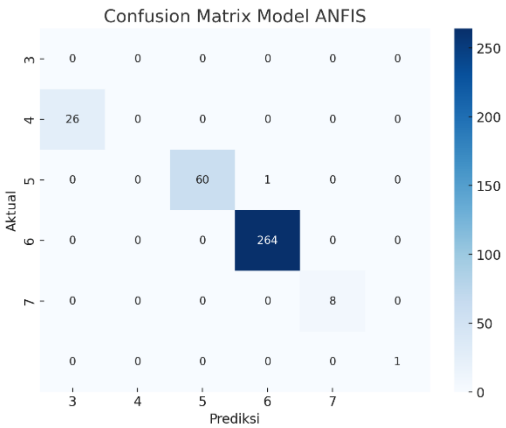

Fig 9 Confusion Matrix-ANFIS

Based on the confusion matrix, the model performs very well in recognizing the majority categories; however, it failed to identify the Positive sentiment, with precision and recall values of 0.000. This shortcoming is attributed to the imbalanced distribution of the data.

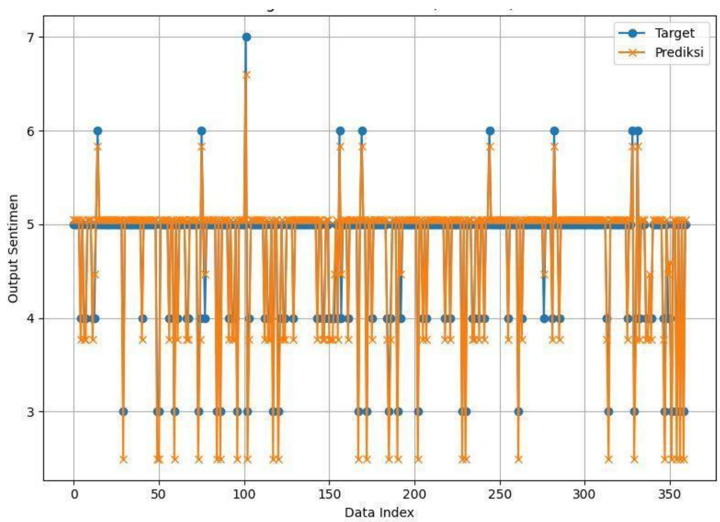

Fig 7 Target and Prediction Graph

The chart in Figure 7 shows that the majority of data with the target sentiment Strongly Positive were correctly predicted by the model. Several data points with target sentiments Weakly Negative and Weakly Positive were also predicted accurately. Although the number of data in these categories is limited, the model was still able to recognize them correctly. The ANFIS model produced an MSE of 0.0341 and an RMSE of 0.1848. This indicates that, on average, the model's prediction error was only about 0.18 points from the actual target values, suggesting that the ANFIS predictions are highly consistent with the ground truth.

Padmaja [19] demonstrated that integrating ANFIS with a Genetic Algorithm (GA) significantly improved sentiment-analysis accuracy from 87% to 93%, while also yielding high precision and recall for both categories. Yazdani et al. [4] compared various membership functions within ANFIS and obtained accuracy of 91.57%, precision of 92.31%, recall of 95.18%, and an F-score of 92.94%. Vashishtha et al. [20] developed MultipLe ANFIS, a lexicon-based neuro-fuzzy system (incorporating VADER, AFINN, and SentiWordNet) for sentiment classification on Twitter. This approach outperformed conventional fuzzy methods and other deep-learning techniques, as evidenced by its lower test RMSE values.

Previous studies [21]–[30] indicate that the application of ANFIS has largely been limited to predictive domains, such as school enrollment in Indonesia—where it achieved R^2 values as high as 0.99 and low MSE—or commodity price forecasting, which proved more accurate and interpretable. In the context of Indonesian sentiment analysis, studies employing FIS reported an average accuracy of 68.83%. However, to date, no literature has been found that explores the use of ANFIS in this domain.

4. CONCLUSION

Both FIS and ANFIS are suitable for sentiment analysis of the Kabinet Merah Putih. ANFIS, however, is superior in accuracy and adaptability. FIS is simpler but less adaptive. Future work: solve class imbalance and optimize membership functions. This study highlights the superiority of ANFIS over FIS in multi-level sentiment analysis, offering a reliable framework to monitor public opinion and support evidence-based policymaking.

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