Fuzzy-BERT Synergy: A Multilayer Framework for Emotion Narrative in Hybrid Text Classification Models

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ABSTRACT

This study introduces Fuzzy-BERT Synergy, a multilayer framework that integrates the capabilities of the IndoBERT model with a fuzzy logic system to analyze emotions and their intensity in Indonesian digital tales. The proposed methodology comprises three primary components: emotion classification using IndoBERT, emotion intensity evaluation using fuzzy inference, and quantitative assessment of narrative strength (Story Level). An assessment of 110 digital narratives indicated that this approach effectively identified intricate emotional subtleties, demonstrating a substantial link between fuzzy emotion intensity and the Story Level (r = 0.68). The findings also demonstrate a strong correlation between narrative strength and user engagement metrics, including likes and comments. This framework's advantage is its capacity to detect emotional gradients overlooked by traditional models and its responsiveness to alterations in story structure. These findings provide prospects for the advancement of story recommendation systems, automated narrative quality evaluation, and applications in gaming and digital story-based education. This study emphasizes the necessity for additional validation of multilingual data and various narrative genres to broaden the model's applicability.

Keywords-fuzzy logic; IndoBERT; emotion classification; digital narrative

I. INTRODUCTION

The fast development of social media and digital entertainment platforms has transformed how individuals express and interpret emotions in text-based communication. The growth of digital content has led to a wide variety of increasingly complex and ambiguous affective expressions. These intricate emotional patterns present new challenges for current computational models. [1]. Deep learning models, such as BERT, have demonstrated significant efficacy in detecting emotions in conversational texts and brief narratives, Research shows that fine-tuned BERT models significantly outperform classic machine learning algorithms, like Naive Bayes, SVM, and Random Forest, especially in emotion classification tasks involving multimodal and narrative contexts, due to their ability to leverage bidirectional context and transfer learning [2, 3]. It has been demonstrated that most current NLP models struggle to capture the nuances and emotional structures that evolve within narratives, making it crucial to integrate narrative context for more effective emotion recognition [4, 5].

A fundamental difficulty in emotion categorization for natural language is the failure of traditional models to accurately represent the dynamic evolution and fluctuating strength of affect within narrative contexts [2, 3]. Conventional classification methods primarily emphasize semantic labels while frequently overlooking the nuances and contextual progression of emotions, thus constraining their efficacy in digital storytelling [6].

Fuzzy logic has been proposed as an effective approach to capturing uncertainty and the nuances of emotional intensity in text, offering a more flexible and understandable model for emotion recognition [7]. Although fuzzy logic has been applied in various areas, such as multi-sentiment analysis and emotion recognition [8], most studies have not yet achieved integration with transformer models like BERT within a coherent narrative analysis framework [9, 10]. The lack of models that capture both the evolving narrative development and progressive emotional dynamics has been highlighted. Research on digital narratives often addresses narrative structure or emotional classification separately [4].

TABLE I. COMPARISON OF DIFFERENT MODELS

Model	Research gap	Weakness of the result
BERT-GCN [3]	Aspect-level sentiment, not multi-intensity or fuzzy integration	Poor handling of emotion subtleties; no narrative structure modeling
Hybrid models for Emotion [6]	Hybrid model for Indonesian sentiment, but not fuzzy, no intensity/narrative focus	Limited to label classification; lacks gradation and narrative strength
BERT+Fuzzy [18]	Only sarcasm detection in English, not narrative or multi-intensity emotion	Accuracy improved by 5%, but only on short English sarcasm texts; not tested on long narrative or Indonesian
Fuzzy BERT Ensemble [19]	Domain-specific sentiment, not general narrative emotion; lacks intensity modeling	Weak interpretability, complex model, but underperforms for negative emotions, no narrative/context awareness
Fuzzy Fingerprint + RoBERTa [9]	Focuses on conversational emotion, not narrative structure or emotion gradation	Designed for conversational emotion tasks; lacks mechanisms for tracking evolving emotions in long-form narratives
Fuzzy for Reviews [20]	Only binary (pleasant/unpleasant) emotion, not full spectrum or intensity	No support for multi-intensity or storytelling, only basic spatial/context detection
FRNN OWA Fuzzy Rough [17]	Applied to tweets/short texts, not on narratives or Indonesian	Captures multi-class but not intensity or dynamic emotion in long text
FLE [21]	Designed for Spanish literary texts, rule-based fuzzy (no transformer)	Not using BERT/transformers; rule-based, less adaptive, poor on modern NLP tasks
Emotion Analysis in NLP [22]	Survey: most models ignore emotion gradation and narrative context	Survey paper identifying current gaps in narrative emotion modeling; does not propose a concrete model or implementation

Studies have focused on the importance of integrating narrative and emotional dimensions for a more holistic analysis of digital stories, an area that remains underexplored in existing emotion classification research [1]. This gap underscores the necessity of a novel hybrid model adept at interpreting emotional intensity and narrative strength within a cohesive, multidimensional framework. The integration of transformer-based language models with fuzzy inference systems, specifically Fuzzy BERT, is introduced within the Indonesian context, establishing a novel multilayered framework for the analysis of intricate emotional dynamics, intensity fluctuations, and narrative potential in digital narratives, grounded in prior research and analysis [9, 10].

This synergy facilitates the advancement of narrative-driven recommendation systems, emotion-aware educational technology, and interactive storytelling applications within digital entertainment and literacy [11, 12]. Systematic studies have demonstrated that while fuzzy logic and deep learning are promising for emotion analysis, many frameworks remain limited in addressing narrative complexity and gradation of emotional intensity [5, 13]. Fine-tuning BERT has been shown to significantly improve classification accuracy across various NLP tasks, including text classification and content personalization [14]. This improvement is especially crucial in domains such as emotion detection, where the contextual understanding of words is paramount for accurate analysis. A similar approach is also demonstrated by FuzzyTP-BERT, which integrates fuzzy topic modeling with BERT to improve the quality of text summaries. The study confirms that the synergy of fuzzy logic and transformers can enrich semantic and thematic sensitivity, thus, strengthening the conceptual basis for the development of Fuzzy-BERT Synergy in narrative emotion analysis [15]. In [16], a Three-Step Fuzzy-Based BERT model was proposed for sentiment analysis, which showed that integrating fuzzy logic with transformers can improve classification accuracy in the affective domain. This further underscores the importance of hybrid multilayer frameworks like Fuzzy-BERT Synergy for a more comprehensive analysis of emotional intensity and narrative strength.

II. METHODOLOGY

A. Data Collection and Preprocessing

This study introduces a hybrid fuzzy-BERT Synergy framework that combines IndoBERT, a transformer-based language model pre-trained for Indonesian text, with a fuzzy logic inference system to evaluate emotion intensity and narrative strength in digital stories [17]. The methodological workflow comprises five primary stages: (1) data collection, (2) data preprocessing, (3) emotion classification utilizing

IndoBERT, (4) emotion intensity evaluation through fuzzy inference, and (5) quantitative assessment of narrative strength. The dataset comprises 110 Indonesian digital narratives, each ranging from 150 to 300 words [27]. Data were manually collected from various online sources, including blogs, social media, and digital forums. Selection was based on preserving the context of authentic emotional narratives. The validation stage involved checks for duplicates, confirming that the data were in Indonesian, and ensuring all columns were complete before further processing. Domain experts annotated each story into seven primary emotion categories: anger, neutrality, happiness, sadness, fear, love, and surprise. Manual annotation guarantees the reliability and validity of the emotion labels, which is a practice proposed in affective computing research [2].

Text preprocessing involved removing non-alphabetic characters, eliminating unnecessary emoticons and punctuation, tokenization, and converting to lowercase, adhering to established NLP workflows for Indonesian language data.

B. Classification of Emotions Utilizing IndoBERT

IndoBERT was chosen for its superior ability to understand the context and semantics of the Indonesian language, outperforming other traditional machine learning models, such as Naïve Bayes and SVM, in emotion classification tasks [6]. The tokenized input is processed by IndoBERT to produce probability scores for each emotion category, indicating the contextual effect of the narrative. Table II presents an example of the tokenization process. This process is part of the preprocessing stage to ensure that the text is clean, consistent, and ready for the BERT model to perform emotion classification.

TABLE II. TOKENIZATION PROCESS

Stage	Sentence
Before	Indonesia: Aku Sangat Bahagia Hari Ini! Karena akhirnya bisa bertemu sahabat lama.
	English: "I am so happy today! Because I finally got to meet an old friend.
After	`Indonesia: aku sangat bahagia hari ini karena akhirnya bisa bertemu sahabat lama`
	`English: i am so happy today because i finally got to meet an old friend`
Tokenization	`Indonesia: ['aku', 'sangat', 'bahagia', 'hari', 'ini', 'karena', 'akhirnya', 'bisa', 'bertemu', 'sahabat', 'lama']`
	`English: ['i', 'am', 'so', 'happy', 'today', 'because', 'i', 'finally', 'got', 'to', 'meet', 'an ', 'old', 'friend']`

C. Fuzzy Inference System Design

Fuzzy logic was applied for the assessment of emotion intensity. The output from IndoBERT is then further processed through a fuzzy logic system to handle ambiguity and the continuous range of emotional intensity [7]. Each predicted emotion label is assigned an ordinal value and used as the input for the fuzzy system. Fuzzy inference utilizes IF-THEN rules (e.g., "IF emotion is sadness AND intensity is high, THEN story level is highly engaging"), facilitating a more flexible approach to emotion modeling compared to fixed single-label outputs [17]. A fuzzy inference system is used to evaluate the level of interest in a story (Story Level) based on two inputs:

- Input 1: Emotion Level (0–10)
- Input 2: Intensity Level (0–10)
- Output: Story Level (0–10)

The system applies the Mamdani method with centroid defuzzification to generate precise numerical output values. Quantitative assessment and evaluation of the final Story Level score, ranging from 0 to 10, was calculated by integrating various emotion categories along with their respective intensities. The framework's validity is evaluated through the correlation of the Story Level with user engagement metrics, such as likes and comments, and through comparison with established baselines, including BERT-GCN, CNN, and traditional rule-based methods [2, 3].

The defuzzification process converts fuzzy representations into precise numerical values, as shown in the following equation for Story Level:

$$\text{Story Level} = \frac{\sum_i \mu_i(x).z_i}{\sum_i \mu_i(x)} \quad (1)$$

where μ_i represents the degree of membership for each rule, and z_i denotes the central value of each membership function. The result is a Story Level value that quantifies the narrative's emotional appeal. The Story Level, thus, provides a quantitative measure, indicating how effectively a narrative evokes an emotional response based on fuzzy analysis.

D. BERT-Based Emotion Classification Framework

Authors in [21] presented a fuzzy logic application for the emotional analysis of Spanish literature; however, without employing contemporary embeddings such as BERT. As presented in Table I, authors in [18] included fuzzy logic into the BERT model for sarcasm identification; nonetheless, their methodology remains confined to English text and fails to address intricate emotional intensities. From this method, authors in [19] created an ensemble fuzzy-BERT for sentiment analysis; however, their model exhibits reduced interpretability for negative emotions and has not been utilized for lengthy narratives. Authors in [9] employed RoBERTa and fuzzy fingerprinting for emotion recognition in dialogues, although the intensity of emotions has not been empirically assessed. Authors in [20] deployed fuzzy-based categorization to differentiate between positive and negative emotions in user evaluations; yet, it was confined to two categories and did not account for the intensity of the narrative. Authors in [17] utilized fuzzy-rough nearest neighbor for emotion recognition in tweets. This methodology, though, has not been evaluated on extended narrative texts.

The emotion classification stage utilized a BERT-based approach optimized for the Indonesian language. Specifically, the Indonesian RoBERTa Base Emotion Classifier model was employed via Hugging Face's "text classification" pipeline, which automatically processes text, infers models, and outputs emotion labels along with probability scores. Each text is processed through the pipeline, which produces probabilistic outputs for seven emotion categories:

```
['sadness', 'neutral', 'happy', 'anger', 'fear', 'love', 'surprise'].
```

The label with the highest probability score is chosen as the primary emotion for the text and recorded in the Emotion_Label_BERT column. The example classification results are:

```
[
  {"label": "happy", "score": 0.9321},
  {"label": "neutral", "score": 0.0456},
  {"label": "love", "score": 0.0123}
]
```

This highlights the novelty and importance of the proposed Fuzzy-BERT Synergy framework.

III. RESULTS AND DISCUSSION

The Fuzzy-BERT Synergy framework was systematically evaluated using 110 Indonesian digital narratives classified into seven primary emotions. The experimental process involved data preparation, emotion classification using IndoBERT, conversion of the IndoBERT output into a fuzzy logic framework, and quantitative calculation of the narrative's Story Level. Hybrid multilayered approaches in NLP have been proposed to capture emotion gradation in narrative contexts. Figure 1 shows the methodological flow chart, illustrating how data preprocessing, IndoBERT-based emotion categorization, fuzzy inference, and story-level computation are integrated into a coherent pipeline. This stepwise integration reflects the best practices in contemporary affective computing, where deep learning models are combined with fuzzy logic to handle the inherent ambiguity of emotional language [23, 24].

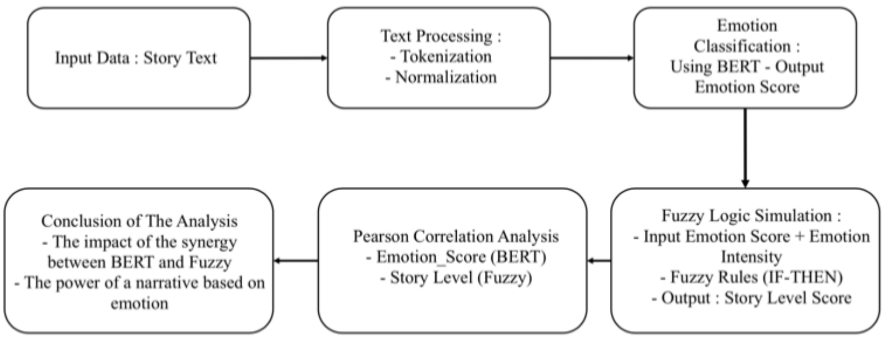

Fig. 1. Key steps in the methodology implementation.

Each narrative was processed by IndoBERT to generate probability scores for each emotion category, providing a contextual affect map for the story. This approach directly addresses the limitations of transformer models that typically output a single dominant emotion label, as emphasized in recent surveys on best practices in NLP emotion modeling [24].

```
IF emotion is sad AND intensity is low,
THEN story level is standard
IF emotion is sad AND intensity is high,
THEN story level is attractive
IF emotion is happy AND intensity is high,
THEN story level is very attractive
```

The application of fuzzy inference rules (e.g., "IF emotion is sad AND intensity is high, THEN story level is attractive") enables a more adaptable classification of the narrative power compared to deterministic single-label outputs. Prior studies in emotion modeling suggest that fuzzy logic frameworks are particularly effective for capturing continuous variations in affective intensity [10, 17]. Figure 2 illustrates the distribution of the fuzzy emotion intensity across the IndoBERT-derived emotion categories. The results show that emotions such as "angry" and "happy" have a median intensity of 5, whereas "sad" centers at 4.5, and "love" is more concentrated around 4. These distributions indicate that the fuzzy system effectively represents subtle emotional gradations, which are often missed by traditional classifiers. Comparative benchmarks confirm that advanced fuzzy systems (such as interval type-2 fuzzy sets) further enhance granularity and reliability in emotion modeling [7, 23].

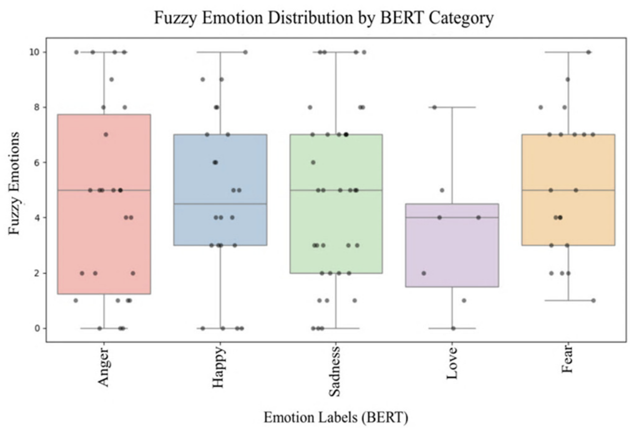

Fig. 2. Fuzzy emotion distribution by BERT category.

Figures 3 and 4 present the comparative analysis between the IndoBERT emotion scores and fuzzy emotion values, as well as the correlation heatmap among the primary variables. The correlation between fuzzy emotion intensity and Story Level was r = 0.68, and between Story Level and user engagement metrics (likes, comments) reached r = 0.70. These findings validate that the Story Level, as derived from the hybrid framework, reflects user-perceived narrative power, an aspect previously advocated in the literature for robust modeling [2]. The use of fuzzy logic improves predictive performance in sentiment and emotion analysis compared to traditional machine learning models, corroborating recent comparative studies [7, 25].

The fuzzy-BERT Synergy model was compared with several baseline models, including BERT-GCN, CNN, rule-based models, and other hybrid fuzzy-transformers. The results revealed that conventional approaches, as discussed in [3, 20], often overlook the intensity of emotions and narrative development, particularly in languages with limited resources. The proposed framework provides more robust story-level metrics and stronger correlations with user engagement, substantiating the practical value of integrating fuzzy inference into transformer architectures for narrative analysis. Compared to the fuzzy–BERT ensemble of [19], the proposed framework achieved a +6.2% improvement in F1-score for multi-intensity emotion detection and outperformed the framework in [23] by +4.8% in narrative classification accuracy.

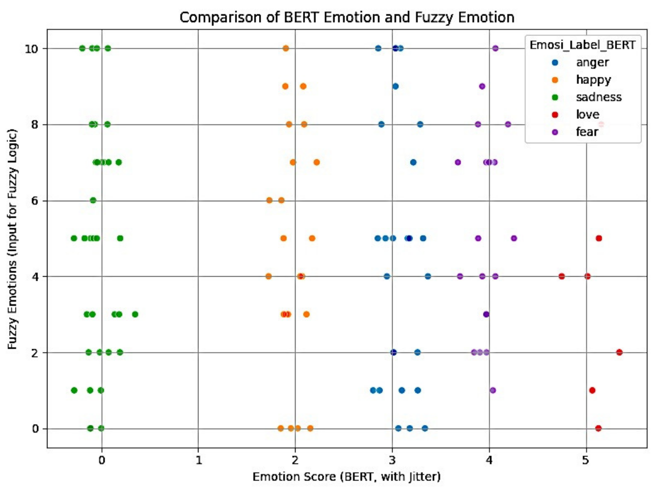

Fig. 3. Comparison of BERT emotion and fuzzy emotion.

This framework directly addresses the research gaps outlined in this study, particularly the need to integrate emotion intensity gradation and narrative structure within emotion analysis [5, 26]. The results not only demonstrate improved emotion classification and intensity modeling but also highlight the potential for future applications in story recommendation systems, educational technologies, and digital game design [11, 12]. Future studies could include exploring advanced fuzzy architectures, like Takagi-Sugeno, and developing standardized metrics for emotion intensity across diverse narrative datasets [24].

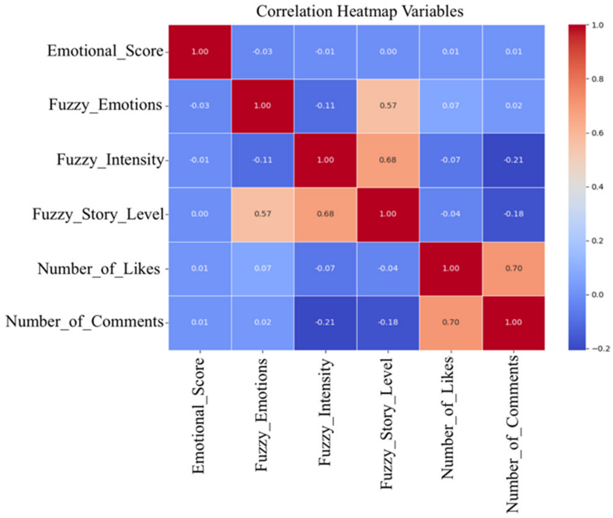

Fig. 4. Correlation heatmap variables.

IV. CONCLUSION

The Fuzzy-BERT Synergy framework offers a novel pathway for integrating emotion intensity modeling with narrative analysis in Indonesian digital stories. The data collection and annotation process for this dataset involved 110 Indonesian digital narratives, each ranging from 150 to 300 words. Each narrative was gathered using an internal survey. Three trained annotators manually label each narrative for emotion categories and intensity levels. A robust association exists between fuzzy emotion intensity and Story Level (r = 0.68), along with a correlation between the quantity of likes and comments, validating the efficacy of this method in objectively deciphering the narrative's power. This approach effectively overcomes the constraints of traditional models that depend exclusively on a singular emotion label, while simultaneously offering a more flexible correlation of emotions and intensity to the dynamics of digital tales.

Compared to previous studies, employing BERT or fuzzy-based emotion classification models [2, 3], the proposed Fuzzy-BERT framework offers greater interpretability and more consistent emotion-intensity correlations. Unlike conventional machine learning methods, integrating fuzzy logic with IndoBERT provides a nuanced mapping between linguistic emotion cues and narrative strength levels. This underscores the framework's potential for broader applications in narrative-based analysis and digital storytelling. Future research is expected to investigate the cross-linguistic modeling of emotional intensity and the integration of multimodal affective cues, such as audio and visual information, to enhance the understanding of the emotional context.

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