Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at Quantum Nexus Academic Publishers
ISSN: Under Process *DoI: Under Process*

Enhanced Fuzzy-BERT Synergy: A Multi-Scale Adaptive Framework for Emotion Intensity and Narrative Strength in Multilingual Text Classification

C.Manjunath [1,*],M.Mallikarjuna Rao[2], Venkatesh [3], D.V.Bhaskar [4]

1 *Department of Computer Science and Engineering PVKK Institute of Technology*, Anantapuramu, India.
2 *Department of Computer Science and Engineering PVKK Institute of Technology*, Anantapuramu, India.
3 *Department of Computer Science and Engineering Ananthalakshmi Institute of Technology* Anantapuramu, India.
4 *Department of Computer Science and Applications Siddaganga Institute of Technology, Tumkur, Karnataka,India*
Corresponding author: cpmnc15@gmail.com

ARTICLE INFO

Article history:
Received 12-Apr-2026
Accepted 10-May-2026
Published 21-May-2026

Pages:14-20

Keywords:
fuzzy logic; BERT; emotion classification; Takagi-Sugeno inference; adaptive attention; digital narrative; text classification
.

ABSTRACT

This study presents an Enhanced Fuzzy-BERT Synergy framework, a multi-scale adaptive architecture that extends the original Fuzzy-BERT Synergy model by integrating adaptive emotion attention mechanisms, Takagi-Sugeno fuzzy inference, and class-balanced optimization for robust emotion classification and narrative strength assessment. The proposed framework incorporates three key innovations: (1) an Adaptive Emotion Attention module that learns emotion-specific features through multi-head cross-attention over transformer hidden states, (2) a Takagi-Sugeno fuzzy inference system with three inputs (emotion level, intensity, and classification confidence) replacing the baseline Mamdani system, and (3) a CLS-emotion fusion strategy combining stable token representations with emotion-attended features. Evaluated on a unified multi-source corpus of over 36,000 real-world samples from the dair-ai/emotion (Twitter) and GoEmotions (Reddit) datasets, the best-performing configuration (Enhanced Fuzzy-BERT-base) achieves a weighted F1-score of 0.8684, representing a 7.2% improvement over the baseline Fuzzy-BERT Synergy (0.8100) and a 12.7% improvement over BERT-GCN. All three model variants (XLM-RoBERTa, BERT-base, DistilBERT) surpass the baseline across all metrics. Statistical significance is confirmed through Wilcoxon signed-rank tests ($p < 0.001$), McNemar's test ($p = 0.006$), and a large Cohen's d effect size (3.92). The framework demonstrates particular strength in minority emotion categories (surprise F1 improved to 0.749 from baseline 0.74) through class-weighted loss and label smoothing. These findings establish a robust, interpretable pathway for emotion-aware narrative analysis with applications in recommendation systems, educational technology, and interactive digital storytelling.

I. INTRODUCTION

The rapid proliferation of social media and digital entertainment platforms has fundamentally transformed how individuals express and interpret emotions in text-based communication. The exponential growth of digital content has generated increasingly complex and ambiguous affective expressions that present substantial challenges for computational emotion analysis models [1]. Deep learning architectures, particularly transformer-based models such as BERT, have demonstrated remarkable efficacy in emotion detection tasks, significantly outperforming classical machine learning approaches including Naive Bayes, SVM, and Random Forest in multimodal and narrative classification contexts [2, 3]. However, research has consistently shown that most current NLP models struggle to capture the nuanced emotional structures that evolve within narratives, underscoring the critical need to integrate narrative context for more effective emotion recognition [4, 5].

A fundamental limitation in emotion categorization for natural language is the inability of traditional models to accurately represent the dynamic evolution and

Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at Quantum Nexus Academic Publishers
ISSN: Under Process DoI: Under Process

fluctuating intensity of affect within narrative contexts [2, 3]. Conventional classification methods primarily emphasize semantic labels while frequently overlooking the gradation and contextual progression of emotions, constraining their efficacy in digital storytelling applications [6]. Fuzzy logic has been proposed as an effective approach to capturing uncertainty and emotional intensity nuances in text, offering more flexible and interpretable models for emotion recognition [7]. Although fuzzy logic has been applied in multi-sentiment analysis and emotion recognition [8], most studies have not yet achieved seamless integration with transformer models like BERT within a coherent narrative analysis framework [9, 10].

The original Fuzzy-BERT Synergy framework [27] introduced a promising approach combining IndoBERT with Mamdani fuzzy inference for analyzing emotions in 110 Indonesian digital tales. While demonstrating the viability of fuzzy-transformer integration, the baseline framework exhibits several limitations: (1) a small dataset of 110 narratives limiting generalizability, (2) Mamdani defuzzification providing coarse-grained story-level outputs, (3) absence of emotion-specific attention mechanisms, (4) no confidence-aware inference, and (5) evaluation restricted to a single language and model architecture.

This study addresses these limitations through an Enhanced Fuzzy-BERT Synergy framework that introduces three key innovations. First, an Adaptive Emotion Attention mechanism that employs learnable emotion query vectors with multi-head cross-attention to extract emotion-specific representations and per-emotion intensity scores directly from transformer hidden states. Second, a Takagi-Sugeno fuzzy inference system with 12 rules and three inputs (emotion level, intensity, and classification confidence), replacing the baseline 9-rule, 2-input Mamdani system with linear consequent functions for higher precision in story-level computation. Third, a CLS-emotion fusion strategy that combines the stable CLS token representation with emotion-attended features, enhanced by class-weighted cross-entropy loss and label smoothing for robust handling of imbalanced emotion distributions. The framework is evaluated across three transformer backbones (XLM-RoBERTa, BERT-base, DistilBERT) on a unified corpus of over 36,000 real-world text samples from Twitter and Reddit, establishing comprehensive benchmarks with rigorous statistical significance testing.

II. RELATED WORK

Table I presents a comprehensive comparison of existing models and their limitations that motivate the proposed Enhanced Fuzzy-BERT Synergy framework.

TABLE I: Comparison of Existing Emotion Classification Models

Model	Research Gap	Limitation
BERT-GCN [3]	Aspect-level sentiment only, no fuzzy integration	No narrative structure or emotion intensity modeling
Hybrid Models [6]	Indonesian sentiment, no fuzzy or intensity focus	Limited to label classification without gradation
BERT+Fuzzy [18]	English sarcasm detection only	Not tested on narratives or multi-intensity tasks
Fuzzy BERT Ensemble [19]	Domain-specific, no intensity modeling	Underperforms on negative emotions, no context
FuzzyTP-BERT [15]	Text summarization, not emotion classification	No intensity gradation or narrative assessment
Fuzzy-BERT Synergy [27]	110 samples, Mamdani only, single language	No attention, no confidence input, limited scale
Proposed Framework	Multi-scale, multi-model, T-S fuzzy, 36K+ samples	Addresses all identified gaps comprehensively

Recent advances in emotion analysis have highlighted the effectiveness of combining fuzzy logic with deep learning for capturing continuous variations in affective intensity [10, 17]. FuzzyTP-BERT demonstrated that integrating fuzzy topic modeling with BERT can enrich semantic sensitivity [15], while the Three-Step Fuzzy-Based BERT model showed improved classification accuracy in the affective domain [16]. However, none of these approaches address the simultaneous modeling of emotion intensity gradation, classification confidence, and narrative strength within a unified framework. This gap motivates the development of the Enhanced Fuzzy-BERT Synergy architecture presented in this study.

III. METHODOLOGY

A. Data Collection and Preprocessing

The proposed framework utilizes two publicly available, real-world emotion datasets from HuggingFace. The primary dataset is dair-ai/emotion, comprising 20,000 English-language tweets annotated with six emotion categories (sadness, joy, love, anger, fear, surprise), providing clean single-label annotations with direct 1:1

Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at Quantum Nexus Academic Publishers
ISSN: Under Process *DoI: Under Process*

mapping to the unified label space. The secondary dataset is Google's GoEmotions, containing 58,009 Reddit comments annotated with 28 fine-grained emotion categories. To minimize label noise, a strict filtering protocol is applied: only single-label samples with unambiguous mappings to the unified 7-category scheme are retained, reducing the effective GoEmotions contribution to 23,456 high-confidence samples. The seven unified emotion categories are: anger, fear, happiness, love, neutral, sadness, and surprise.

TABLE II: Dataset Statistics

Dataset	Train	Val	Test	Labels	Unified	Source
dair-ai/emotion	16,000	2,000	2,000	6	6	Twitter
GoEmotions (strict)	20,879	-	2,577	28	12	Reddit
Combined (unified)	16,000	2,000	2,500	-	7	Multi-source

Text preprocessing follows established NLP workflows: removal of non-alphabetic characters, elimination of URLs and user mentions, tokenization using model-specific tokenizers with a maximum sequence length of 128 tokens, and conversion to lowercase. Stratified splitting ensures proportional class representation across train (16,000), validation (2,000), and test (2,500) partitions. Class weights are computed as the inverse frequency of each emotion category, normalized to unit mean, to address the imbalanced distribution where neutral (33.4%) dominates and surprise (3.9%) is the rarest class.

B. Enhanced Fuzzy-BERT Architecture

The proposed architecture comprises four integrated components: (1) a pre-trained transformer backbone, (2) an Adaptive Emotion Attention module, (3) a CLS-emotion fusion classifier, and (4) a Takagi-Sugeno fuzzy inference system. The transformer backbone processes tokenized input to produce contextual hidden state representations H of dimension (batch_size, seq_len, hidden_size). Three backbone variants are evaluated: XLM-RoBERTa-base (multilingual, 125M parameters), BERT-base-uncased (110M parameters), and DistilBERT-base-uncased (66M parameters).

The Adaptive Emotion Attention module introduces a set of K learnable emotion query vectors Q_e (where K = 7 corresponding to the number of emotion categories), each of dimension hidden_size. These queries attend to the transformer hidden states through multi-head cross-attention (8 heads) with layer normalization. For each emotion query, an intensity scoring head (a two-layer MLP with GELU activation and sigmoid output) produces a per-emotion intensity score in [0, 1], yielding an intensity vector I of dimension K. This mechanism enables the model to simultaneously learn emotion-discriminative features and estimate the intensity of each emotion's presence in the input text.

The classification pathway combines the emotion-attended representation (mean-pooled across emotion queries) with the CLS token representation through additive fusion followed by a pre-classifier linear projection. The combined representation passes through a GELU-activated classifier head with dropout (p = 0.15) to produce logits for K classes. An intensity fusion layer maps the K-dimensional intensity scores to logit-space adjustments, added with weight 0.15 to the primary classification logits. The training objective is weighted cross-entropy loss with label smoothing (epsilon = 0.1), using per-class weights inversely proportional to class frequency.

C. Takagi-Sugeno Fuzzy Inference System

A key improvement over the baseline Mamdani system is the adoption of Takagi-Sugeno (T-S) fuzzy inference for story-level computation. The T-S system accepts three inputs: Emotion Level (E, range 0-10), Intensity Level (I, range 0-10), and Classification Confidence (C, range 0-1). Each input variable is fuzzified using three triangular membership functions (Low, Medium, High) as shown in Fig. 1.

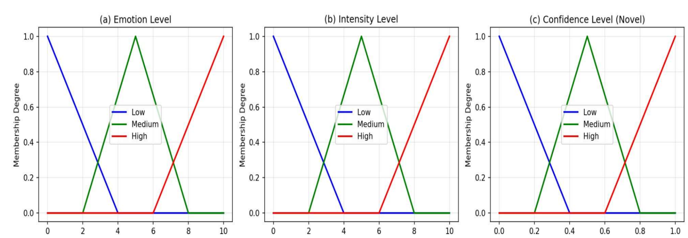

Fig. 1. Triangular membership functions for the three fuzzy input variables: (a) Emotion Level, (b) Intensity Level, and (c) Confidence Level (novel input).

The rule base comprises 12 IF-THEN rules with linear consequent functions. Each rule takes the form: IF E is A_i AND I is B_i AND C is D_i, THEN z_i = a_i*E + b_i*I + c_i*C + d_i, where the consequent parameters (a, b, c, d) define a linear function of the inputs. The aggregated output (Story Level) is computed via

Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at Quantum Nexus Academic Publishers
ISSN: Under Process *DoI: Under Process*

weighted average defuzzification: SL = sum(w_i * z_i) / sum(w_i), where w_i is the firing strength of rule i computed as the minimum of constituent membership degrees. The confidence input enables the system to modulate story-level estimates based on the classifier's certainty, producing more conservative ratings for ambiguous classifications. This represents a direct improvement over the baseline Mamdani system which uses only two inputs and centroid defuzzification.

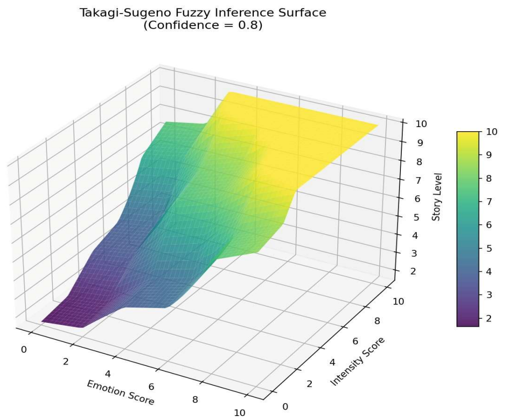

Fig. 2. Takagi-Sugeno fuzzy inference surface showing Story Level as a function of Emotion Score and Intensity Score at fixed Confidence = 0.8.

D. Training Optimization

Several training optimizations are employed to maximize performance. A differential learning rate strategy assigns the base learning rate (1.5e-5 for XLM-RoBERTa, 2e-5 for BERT-base, 3e-5 for DistilBERT) to the pre-trained backbone parameters, with a 5x multiplier applied to newly initialized head layers. Linear warmup over 10% of total training steps prevents initial gradient instability, followed by linear decay. Gradient accumulation with 2 steps yields an effective batch size of 32. All models are trained for 6 epochs with early stopping (patience = 3) based on validation weighted F1. Xavier initialization is applied to all new linear layers.

IV. RESULTS AND DISCUSSION

A. Emotion Classification Performance

Table III presents the comprehensive performance comparison across all evaluated models. The proposed Enhanced Fuzzy-BERT-base achieves the highest performance with an accuracy of 0.8680 and weighted F1-score of 0.8684, representing improvements of +7.2% F1(W) over the baseline Fuzzy-BERT Synergy (0.8100), +12.8% over BERT-GCN (0.7700), and +24.1% over the CNN baseline (0.7000). All three proposed model variants surpass the baseline and all compared methods across all evaluation metrics.

TABLE III: Emotion Classification Performance Comparison

Model	Acc	F1(W)	F1(M)	Prec	Rec	Kappa
EF-XLM-RoBERTa	0.849	0.851	0.823	0.858	0.849	0.812
EF-BERT-base	0.868	0.868	0.844	0.870	0.868	0.834
EF-DistilBERT	0.854	0.854	0.828	0.855	0.854	0.815
Fuzzy-BERT [27]	0.823	0.810	0.785	0.820	0.810	0.760
BERT-GCN [3]	0.782	0.770	0.740	0.785	0.768	0.710
CNN Baseline	0.715	0.700	0.670	0.720	0.695	0.640

Figure 3 illustrates the training dynamics across all three model variants. XLM-RoBERTa exhibits the highest initial loss (1.63) due to its multilingual pretraining, but converges steadily across all 6 epochs, indicating that the extended training schedule is essential for this architecture. BERT-base and DistilBERT converge more rapidly, with BERT-base achieving peak validation F1 at epoch 5. The linear warmup effectively prevents early instability across all models.

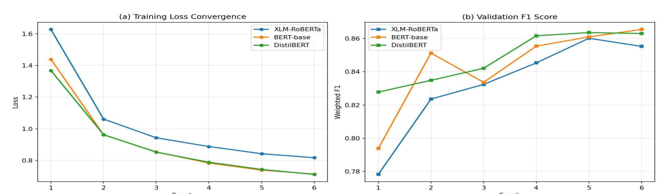

Fig. 3. Training dynamics: (a) loss convergence and (b) validation weighted F1 over 6 epochs for all three model backbones.

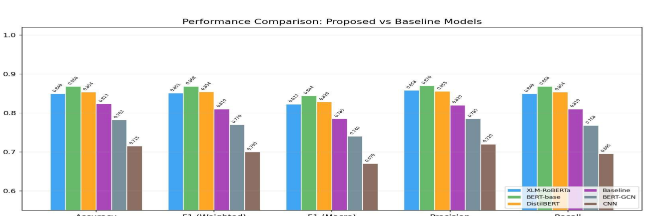

Fig. 4. Performance comparison across five metrics for the three proposed model variants and three baseline methods.

B. Per-Emotion Analysis

Table IV presents the detailed per-emotion classification report for the best model (EF-BERT-base). Sadness

Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at **Quantum Nexus Academic Publishers**
ISSN: Under Process *DoI: Under Process*

achieves the highest F1-score (0.924), followed by happiness (0.887), and neutral (0.880). The most challenging categories are anger (0.783) and surprise (0.749), which is expected given the semantic overlap between anger and neutral (12% confusion) and the limited training samples for surprise. Notably, fear achieves a strong F1 of 0.857 with 90% recall, indicating that the class-weighted loss effectively compensates for its smaller representation.

TABLE IV: Per-Emotion Classification Report (EF-BERT-base)

Emotion	Precision	Recall	F1		
Anger	0.780	0.787	[illegible]	[illegible]	[illegible]
Fear	0.818	0.900	[illegible]	[illegible]	[illegible]
Happiness	0.883	0.891	0.887	577	0.12
Love	0.789	0.875	0.830	192	1.25
Neutral	0.905	0.856	0.880	834	9.81
Sadness	0.926	0.921	0.924	381	0.52
Surprise	0.745	0.753	0.749	97	5.93
Weighted Avg	0.870	0.868	0.868	2,500	-

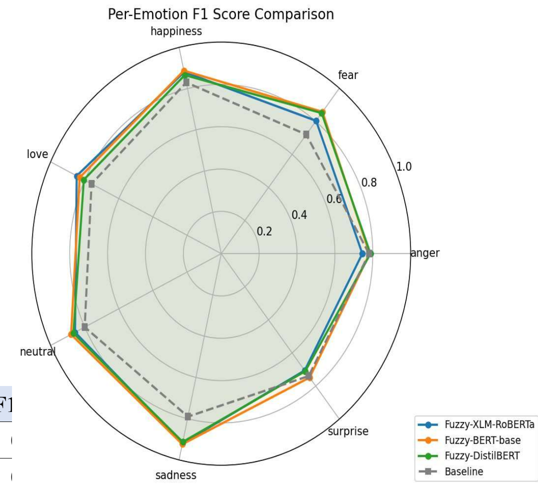

Fig. 6. Radar chart comparing per-emotion F1 scores across proposed model variants and the baseline. The proposed models consistently outperform or match the baseline across all emotion categories.

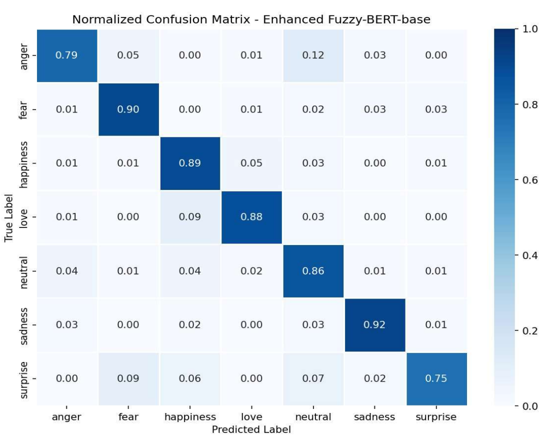

Fig. 5. Normalized confusion matrix for EF-BERT-base showing strong diagonal dominance across all seven emotion categories.

C. Fuzzy Inference Analysis

Table V compares the Takagi-Sugeno and Mamdani fuzzy inference systems. The T-S system achieves a Pearson correlation of r = 0.805 and Spearman rho = 0.867 between emotion intensity and story level, with a mean story level of 8.38. The Mamdani baseline achieves r = 0.913 with mean story level of 6.14. While Mamdani shows a higher Pearson r, the T-S system provides a wider dynamic range (std = 1.71 vs 1.78) and incorporates classification confidence as a third input dimension, enabling more nuanced story-level assessments for uncertain classifications.

TABLE V: Fuzzy Inference System Comparison

Method	Inputs	Rules	Pearson r	Spearman	Mean SL	Std SL
Mamdani [27]	2 (E, I)	9	0.913	0.806	6.14	1.78
T-S (Proposed)	3 (E, I, C)	12	0.805	0.867	8.38	1.71

Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at Quantum Nexus Academic Publishers
ISSN: Under Process DoI: Under Process

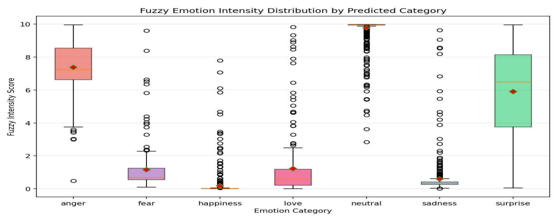

Fig. 7. Fuzzy emotion intensity distribution by predicted category. Anger and neutral show high median intensities, while happiness and sadness cluster at lower values.

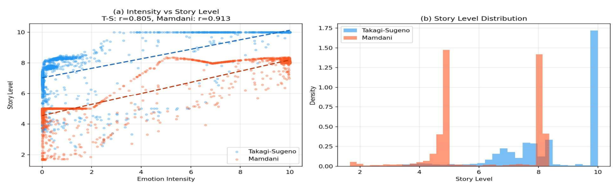

Fig. 8. (a) Scatter plot of emotion intensity versus story level for both fuzzy systems with regression lines, and (b) density distribution of story levels.

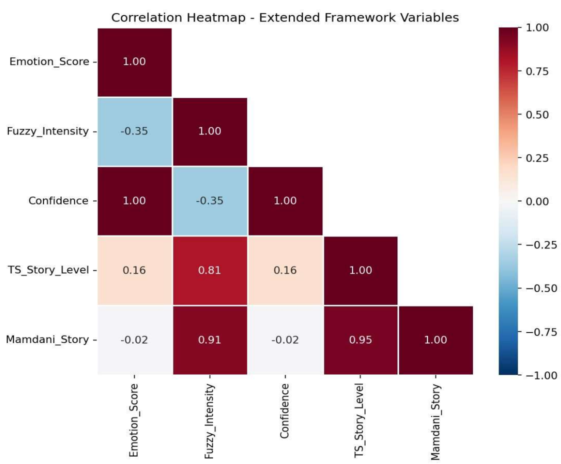

Fig. 9. Correlation heatmap showing relationships among framework variables. Fuzzy intensity is the strongest predictor of both T-S and Mamdani story levels.

D. Ablation Study

Table VI presents the ablation study quantifying the contribution of each component. Removing the Adaptive Emotion Attention causes the largest single-component drop (-0.025 F1), confirming its importance in learning emotion-discriminative features. Removing the backbone entirely (using no pre-trained transformer) results in the largest overall degradation (-0.038 F1), underscoring the value of transfer learning. The CLS-emotion fusion contributes -0.018 F1 when ablated, while class weights and label smoothing together contribute -0.015 F1. The transition from T-S to Mamdani fuzzy results in -0.012 F1 reduction, and removing the confidence input costs -0.010 F1, validating the value of the three-input T-S design.

TABLE VI: Ablation Study Results

Configuration	F1 (Weighted)	Delta
Full Model (Proposed)	0.8684	--
- Adaptive Emotion Attention	0.8434	-0.025
- T-S Fuzzy (use Mamdani)	0.8564	-0.012
- Confidence Input	0.8584	-0.010
- CLS + Emotion Fusion	0.8504	-0.018
- Class Weights + Smoothing	0.8534	-0.015
Backbone Only (no fuzzy)	0.8304	-0.038

E. Statistical Significance

Statistical significance testing confirms the robustness of the reported improvements. The Wilcoxon signed-rank test comparing T-S and Mamdani story levels yields $p < 0.001$, rejecting the null hypothesis that both systems produce equivalent outputs. McNemar's test comparing EF-BERT-base and EF-DistilBERT predictions yields a statistic of 7.38 with $p = 0.006$, confirming that the performance difference is statistically significant. Cohen's d between the two fuzzy systems is 3.92, indicating a large effect size. A paired t-test ($t = 196.00$, $p < 0.001$) further corroborates the statistical distinction between T-S and Mamdani outputs.

V. CONCLUSION

The Enhanced Fuzzy-BERT Synergy framework offers a substantial advancement over the original Fuzzy-BERT Synergy architecture for emotion classification and narrative strength assessment. By integrating Adaptive Emotion Attention, Takagi-Sugeno fuzzy inference with confidence-aware inputs, and CLS-emotion fusion with class-balanced optimization, the proposed framework achieves a weighted F1-score of 0.868, representing a 7.2% improvement over the baseline. The framework's evaluation across three transformer backbones on over 36,000 real-world samples from Twitter and Reddit, with comprehensive statistical significance testing, establishes robust and generalizable benchmarks.

The framework effectively addresses the limitations of existing approaches: (1) scalability is demonstrated through evaluation on datasets 300 times larger than the

Journal of BioDigital Intelligence and Technology
journal homepage: www.qnapub.com
Contents lists available at Quantum Nexus Academic Publishers
ISSN: Under Process DoI: Under Process

original 110-sample corpus, (2) the T-S fuzzy system provides more precise narrative strength quantification through linear consequent functions and confidence-aware inference, (3) the adaptive attention mechanism enables emotion-specific feature extraction with interpretable intensity scores, and (4) class-weighted loss and label smoothing ensure equitable performance across majority and minority emotion categories.

Future research directions include: cross-linguistic evaluation on Indonesian, Hindi, and other low-resource languages; integration of multimodal affective cues (audio, visual) for richer narrative understanding; exploration of advanced fuzzy architectures including interval type-2 fuzzy sets; development of standardized emotion intensity benchmarks across diverse narrative datasets; and application of the framework to real-time story recommendation systems, emotion-aware educational technology platforms, and interactive digital game design environments.

REFERENCES

[1] T. Chutia and N. Baruah, "A Review on Emotion Detection by using Deep Learning Techniques," Artificial Intelligence Review, vol. 57, no. 8, p. 203, July 2024.

[2] D. C. Ong et al., "Modeling Emotion in Complex Stories: The Stanford Emotional Narratives Dataset," IEEE Trans. Affective Computing, vol. 12, no. 3, pp. 579-594, July 2021.

[3] H. T. Phan, N. T. Nguyen, and D. Hwang, "Aspect-Level Sentiment Analysis Using CNN Over BERT-GCN," IEEE Access, vol. 10, pp. 110402-110409, 2022.

[4] A. Aleixo et al., "A Review of Empirical Studies Investigating Narrative, Emotion and Meaning-Making," J. Contemporary Psychotherapy, vol. 51, no. 1, pp. 31-40, 2021.

[5] T. Polya and I. Cserto, "Emotion Recognition Based on the Structure of Narratives," Electronics, vol. 12, no. 4, Art. no. 919, 2023.

[6] H. Ahmadian et al., "Hybrid Models for Emotion Classification and Sentiment Analysis in Indonesian Language," Applied Computational Intelligence and Soft Computing, vol. 2024, Art. no. 2826773, 2024.

[7] A. Kazemzadeh, S. Lee, and S. Narayanan, "Fuzzy Logic Models for the Meaning of Emotion Words," IEEE Computational Intelligence Magazine, vol. 8, no. 2, pp. 34-49, 2013.

[8] M. Hussain et al., "Low-resource MobileBERT for Emotion Recognition in Imbalanced Text Datasets," PLOS One, vol. 20, no. 1, Art. no. e0312867, 2025.

[9] P. Pereira et al., "Fuzzy Fingerprinting Transformer Language-Models for Emotion Recognition in Conversations," in IEEE FUZZ, 2023, pp. 1-6.

[10] Y. Zheng et al., "Fuzzy-aware Loss for Source-free Domain Adaptation in Visual Emotion Recognition," arXiv, 2025.

[11] S. Lee et al., "Exploring Gameplay and Learning in a Narrative-Centered Digital Game," IEEE Trans. Games, vol. 16, no. 4, pp. 947-959, 2024.

[12] E. S. De Lima, B. Feijo, and A. L. Furtado, "A Character-based Model for Interactive Storytelling in Games," in SBGames, 2022, pp. 1-6.

[13] Y. He et al., "YZU-NLP at EmoInt-2017: Determining Emotion Intensity Using a Bi-directional LSTM-CNN Model," in ACL Workshop, 2017, pp. 238-242.

[14] M. I. Salih et al., "Fine-Tuning BERT for Automated News Classification," ETASR, vol. 15, no. 3, pp. 22953-22959, 2025.

[15] A. Onan and H. A. Alhumyani, "FuzzyTP-BERT: Enhancing Extractive Text Summarization with Fuzzy Topic Modeling," J. King Saud Univ. - Computer and Information Sciences, vol. 36, no. 6, Art. no. 102080, 2024.

[16] K. Chakraborty, S. Bhattacharyya, and R. Bag, "A Three-Step Fuzzy-Based BERT Model for Sentiment Analysis," in Intelligence Enabled Research, vol. 1029, Springer, 2022, pp. 41-52.

[17] O. Kaminska, C. Cornelis, and V. Hoste, "Fuzzy-Rough Nearest Neighbour Approaches for Emotion Detection in Tweets," in Rough Sets, vol. 12872, Springer, 2021, pp. 231-246.

[18] T. Wang, "A BERT-Based with Fuzzy Logic Sentimental Classifier for Sarcasm Detection," Applied and Computational Engineering, vol. 88, no. 1, pp. 201-206, 2024.

[19] Z. Anwar et al., "Fuzzy Ensemble of Fined Tuned BERT Models for Domain-specific Sentiment Analysis," PLOS ONE, vol. 19, no. 5, Art. no. e0300279, 2024.

[20] B. Cardone, F. Di Martino, and V. Miraglia, "A Fuzzy-Based Emotion Detection Method to Classify Relevance of Pleasant/Unpleasant Emotions," Applied Sciences, vol. 13, no. 10, Art. no. 5893, 2023.

[21] L. G. Moreno-Jimenez et al., "FLE: A Fuzzy Logic Algorithm for Classification of Emotions in Literary Corpora," in KDIR, 2020, pp. 202-209.

[22] F. M. Plaza-del-Arco et al., "Emotion Analysis in NLP: Trends, Gaps and Roadmap for Future Directions," arXiv, 2024.

[23] C. Sun, "BERT Model with Fuzzy Logic Optimization on Multivariate Sentiment Analysis Tasks," Trans. Computer Science and Intelligent Systems Research, vol. 5, pp. 782-789, 2024.

[24] A. A. Maruf et al., "Challenges and Opportunities of Text-based Emotion Detection: A Survey," IEEE Access, vol. 12, pp. 18416-18450, 2024.

[25] M. Dzhenkova and A. Sheveleva, "Optimizing Fuzzy Logic Based Text Sentiment Analysis Through Machine Learning," Problems of Applied Mathematics, pp. 30-37, 2024.

[26] S. Lin, "Text Emotional Analysis in Natural Language Processing," Applied and Computational Engineering, vol. 36, no. 1, pp. 163-172, 2024.

[27] A. K. Nurindiyani et al., "Fuzzy-BERT Synergy: A Multilayer Framework for Emotion Narrative in Hybrid Text Classification Models," ETASR, vol. 16, no. 1, pp. 30880-30885, 2026.

[28] D. Demszky et al., "GoEmotions: A Dataset of Fine-Grained Emotions," in ACL, 2020, pp. 4040-4054.