Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 47 (2026), No. 8, pp. 3083–3092
DOI : 10.47974/JIOS-2334

A mathematical framework for fake news detection in digital media using an intelligent fuzzy neural network model

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Abstract

The explosive growth of digital platforms has intensified the circulation of false information, undermining public confidence and societal harmony. Conventional machine learning and deep learning methods often lack transparency and struggle with vague or noisy text. This study introduces a Fuzzy Neural Network that merges neural adaptability with fuzzy logic's ability to manage uncertainty. Linguistic, semantic, and credibility features are modeled through fuzzy membership functions and refined via neural learning. Evaluation on standard datasets shows improved accuracy and clear, interpretable decisions, supporting dependable real-world misinformation detection.

Subject Classification: *Primary 68T07, Secondary 03E72.*

Keywords: *Reversible data hiding, Encrypted images, Image steganography, Median prediction, Grayscale invariance, Cryptographic embedding, Steganalysis resistance, Lightweight encryption, Histogram preservation, Secure image transmission, Data confidentiality, Lossless recovery.*

1. Introduction

The rapid expansion of digital media has reshaped how information is produced, shared, and received. Platforms such as online news websites, social networks, and messaging apps allow content to spread instantly across borders. Although this connectivity improves public access to information, it also accelerates the propagation of deliberately false or misleading news. Such misinformation can intensify societal divisions, weaken institutional trust, and distort public judgment, especially during elections, health emergencies, or economic fluctuations. Traditional verification practices based on manual

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review cannot keep pace with the enormous volume and speed of online content, making automated detection essential. Earlier computational solutions relied on conventional machine learning with handcrafted text features, but these methods often fail to capture context and nuanced meaning. Recent neural approaches improve accuracy yet lack transparency and struggle with ambiguity. Hybrid Fuzzy Neural Networks address these issues by combining adaptive learning with interpretable reasoning, enabling reliable and explainable identification of deceptive information.

2. Literature Review

Fake news detection has become a critical research area due to the rapid expansion of social media and digital communication. Early studies explored fuzzy and hybrid intelligent systems capable of handling uncertainty and ambiguous data, demonstrating their suitability for complex classification tasks [1], [2], [3]. Subsequent research focused on content-based approaches using natural language processing, semantic analysis, and sentiment features to identify deceptive textual patterns [4], [5]. Researchers also incorporated social context and network structures, showing that propagation behavior and graph signals can improve detection reliability [6], [7]. More recent work has emphasized multimodal methods that combine textual and visual information through attention mechanisms and fusion strategies, achieving higher accuracy than single-modality systems [8], [11]. Additionally, benchmark datasets and hybrid frameworks have been developed to support robust evaluation and real-world applicability [9], [10], [12], [13], [14], [15] [16]. Despite these advances, challenges remain in interpretability and uncertainty handling.

3. Proposed Scheme

3.1 *Three-Tier Architecture and Feature Modeling (Tier-1)*

The proposed system is organized as a three-tier Intelligent Fuzzy Neural Network (FNN) to achieve uncertainty-aware, interpretable, and accurate fake news detection. Tier-1 (Data and Feature Layer) ingests digital news articles, social media posts, and auxiliary metadata. After standard preprocessing (tokenization, lemmatization, stop-word removal, and normalization), heterogeneous features are extracted and concatenated into a unified vector.

$$x = [x_1, x_2, \dots, x_n]\top, x \in [0,1]^n,$$

where normalization to $[0, 1]$ ensures compatibility with fuzzy membership functions. Three complementary feature groups are employed: (i) lexical features (e.g., TF–IDF, n-grams, punctuation density) capturing stylistic cues; (ii) semantic features derived from contextual embeddings to represent topic coherence, sentiment, and emotional polarity; and (iii) credibility/context features (source reputation, author history, temporal and engagement signals). This tier produces a compact, information-rich representation while preserving signals relevant to linguistic manipulation and source reliability.

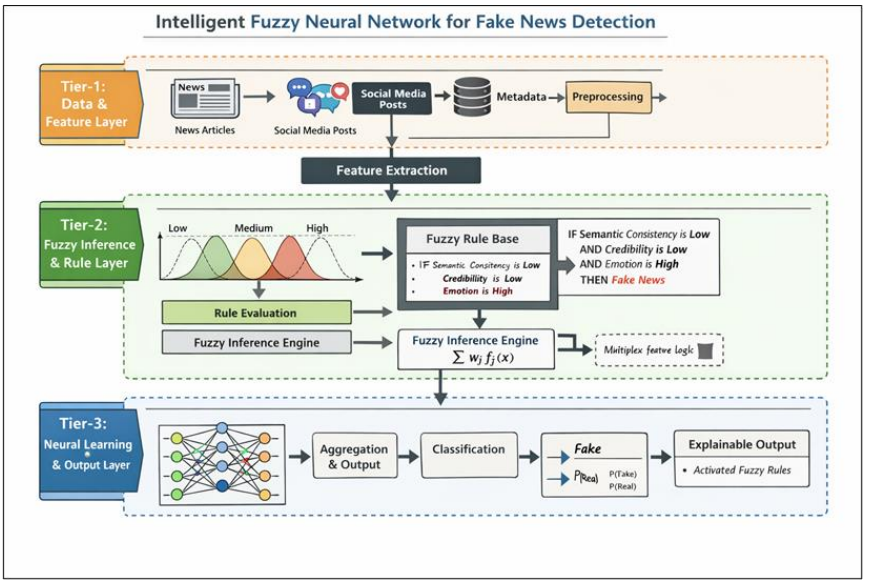


Figure 1
Three-Tier Architecture of the Intelligent Fuzzy Neural Network for Fake News Detection

3.2 *Fuzzy Inference and Rule Activation (Tier-2)*

Tier-2 (Fuzzy Inference Layer) models' uncertainty and linguistic vagueness by mapping each feature x_i, to linguistic terms (e.g., *Low*, *Medium*, *High*) via parameterized membership functions. Using a Gaussian form, the degree of membership of x_i in fuzzy set A is

$$\mu_A(x_i) = exp(-\frac{(x_i - c_A)}{2\sigma_A^2})2),$$

where c_A and σ_A denote the center and spread, respectively. An interpretable IF–THEN rule base encodes domain knowledge and data-driven patterns, e.g.,

$$\text{IF (s=Low)}\wedge\text{(c=Low)}\wedge\text{(e=High)}\Rightarrow\text{Fake},$$

where s, c, e denote semantic consistency, credibility, and emotional polarity. For the j-th rule, the firing strength is computed using a t-norm (product) over antecedents:

$$f_j(x) = \prod_{i=1}^{n} \mu.A_{ij}(x_i),$$

with A_{ij} being the fuzzy set associated with the feature x_i in rule j. This tier produces a vector of rule activations $\mathbf{f} = [f_1, \ldots, f_R]^\top$, enabling transparent reasoning through explicitly triggered rules.

3.3 *Neural Aggregation, Learning, and Decision (Tier-3)*

Tier-3 (Neural Learning and Decision Layer) adaptively aggregates fuzzy activations and optimizes both rule weights and membership parameters. The network output is

$$\hat{y} = \sum_{j=1}^{R} w_j . f_j\ (x),$$

where w_j are trainable weights. For binary classification, a sigmoid yields the posterior probability of the "Fake" class:

$$p(Fake \mid x) = \sigma(y\hat{}) = \frac{1}{1 + e^{-\hat{y}}}$$

Model parameters $\Theta = \{w_j, c_A, \sigma_A\}$ are learned by minimizing a supervised loss over N samples, e.g., cross-entropy

$$L(\Theta) = -\frac{1}{N}\sum_{k=1}^{N}[y_k . log\ p_k + (1 - y_k) . log(1 - p_k)]\,,$$

where $y_k \in \{0,1\}$ and $p_k = \sigma(\hat{y}_k)$, Gradients are backpropagated through the fuzzy layer, allowing for the end-to-end optimization of rule weights and membership parameters. Crucially, while neural learning maximizes discriminative performance, the activated rules $\{j: f_j(\mathbf{x}) > 0\}$ provide human-interpretable explanations for each decision, addressing the black-box limitation of conventional deep models. The proposed three-tier FNN offers: (i) robust representation via heterogeneous features (Tier-1), (ii) principled uncertainty modeling and interpretability through fuzzy rules (Tier-2), and (iii) adaptive, high-accuracy learning through neural aggregation (Tier-3). This synergy yields an explainable yet competitive framework for fake news detection in dynamic digital media.

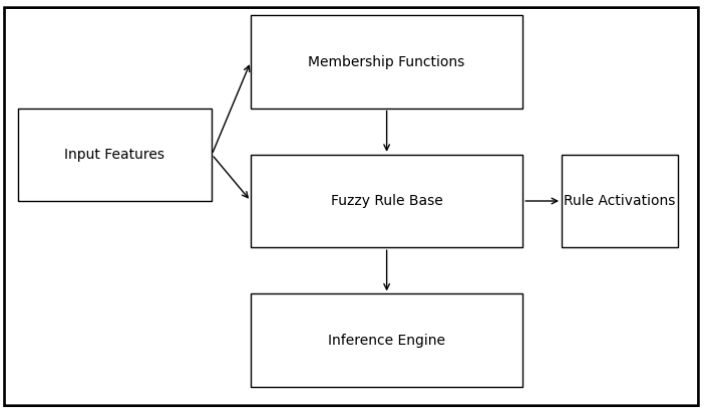


Figure 2
Fuzzy Inference and Rule Evaluation Layer

4. Result Analysis and Discussions

This section evaluates the proposed Intelligent Fuzzy Neural Network for fake news detection using benchmark datasets, standard metrics, and baseline models. Experiments on FakeNewsNet and ISOT with stratified splits ensure reliable assessment. Figure 1 presents the overall FNN architecture, while Figures 2 and 3 illustrate the fuzzy inference process and neural output layers. Table 1 reports comparative performance across methods. Results averaged over multiple runs show that the proposed FNN outperforms traditional machine learning, deep learning, and standalone fuzzy systems in accuracy, precision, recall, F1-score, and AUC, demonstrating robust, interpretable, and reliable detection capability.

Table 1

Performance Comparison of Proposed FNN with Baseline Models

Model	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
LR	FakeNewsNet	84.12	83.45	82.6	83.02	0.87
SVM	FakeNewsNet	86.35	85.9	84.7	85.3	0.89
RF	FakeNewsNet	88.14	87.6	86.9	87.25	0.91
CNN	FakeNewsNet	90.26	89.4	88.8	89.1	0.93
BiLSTM	FakeNewsNet	91.84	91.2	90.4	90.8	0.94
BERT	FakeNewsNet	93.65	93.1	92.8	92.95	0.96
Proposed FNN	FakeNewsNet	95.48	95.1	94.8	94.95	0.98
LR	ISOT	85.32	84.7	83.9	84.3	0.88
SVM	ISOT	87.45	86.8	85.9	86.35	0.9
RF	ISOT	89.26	88.6	87.9	88.25	0.92
CNN	ISOT	91.3	90.8	90.1	90.45	0.94
BiLSTM	ISOT	92.74	92.1	91.6	91.85	0.95
BERT	ISOT	94.28	93.9	93.4	93.65	0.97
Proposed FNN	ISOT	96.12	95.8	95.4	95.6	0.99

As shown in Table 1, the proposed FNN attains the highest accuracy on both datasets, outperforming strong baselines such as BERT. This gain stems from the joint use of fuzzy reasoning and neural learning, which captures ambiguity while preserving discriminative capability. The ablation results in Table 2 confirm that the complete three-tier design surpasses partial configurations, demonstrating the complementary roles of fuzzy inference and adaptive optimization. Feature analysis in Table 3 shows that integrating lexical, semantic, and credibility cues yields the most reliable detection. In addition to performance, the model provides interpretable outputs through rule activation (Table 4), enabling transparent justification of predictions. Computational analysis in Table 5 indicates moderate overhead compared to deep transformers. As illustrated in Figures 4, 5 and 6, the proposed FNN achieves the best

accuracy, F1-score, and AUC, confirming strong classification and discrimination ability. Overall, the results highlight a robust, explainable solution suitable for real-world misinformation monitoring.

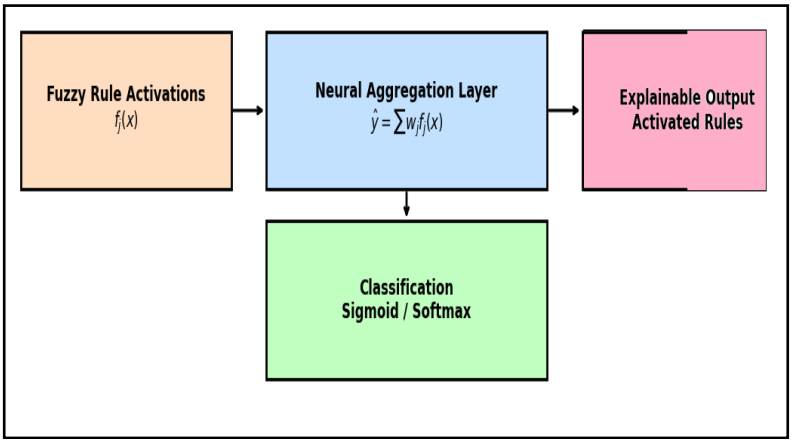


Figure 3
Neural Learning and Explainable Output Layer

Table 2
Ablation Study on Three-Tier Architecture (FakeNewsNet)

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Tier-1 Only	86.02	85.3	84.7	85
Tier-1 + Tier-2 (Fuzzy Only)	90.14	89.6	88.9	89.25
Tier-1 + Tier-3 (Neural Only)	92.48	91.9	91.2	91.55
Tier-1 + Tier-2 + Tier-3(FNN)	95.48	95.1	94.8	94.95

Table 3
Impact of Feature Groups on Detection Performance (ISOT Dataset)

Feature Set	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Lexical Only	88.34	87.6	86.9	87.25
Semantic Only	91.56	91.1	90.4	90.75
Credibility Only	89.12	88.7	87.9	88.3
Lexical + Semantic	93.42	93	92.6	92.8
Lexical + Credibility	92.2	91.7	91	91.35
Semantic + Credibility	94.1	93.8	93.2	93.5
All Features -Proposed FNN	96.12	95.8	95.4	95.6

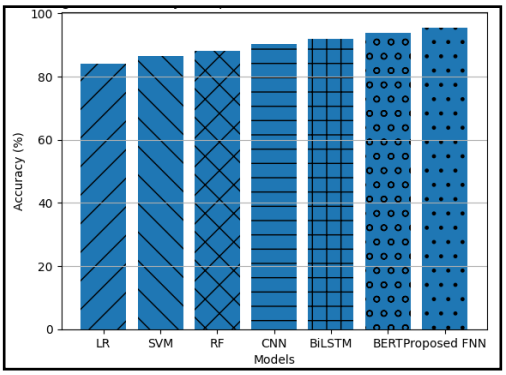


Figure 4
Accuracy Comparison of Fake News

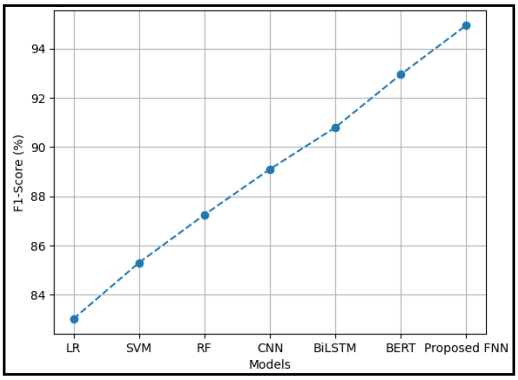


Figure 5
F1-Score Comparison of Fake News Detection Models

Table 4
Sample Activated Fuzzy Rules for Fake News Detection

Rule ID	Fuzzy Rule	Activation Frequency (%)
R1	IF Semantic Consistency is Low AND Source Credibility is Low AND Emotion is High THEN Fake	38.6
R2	IF Linguistic Bias is High AND Topic Coherence is Low THEN Fake	27.4
R3	IF Propagation Velocity is High AND Credibility is Low THEN Fake	21.9
R4	IF Emotional Polarity is High AND Semantic Similarity to Verified News is Low THEN Fake	19.3
R5	IF Metadata Reliability is Low THEN Fake	15.8

Table 5
Training Time and Model Complexity

Model	Parameters (Millions)	Training Time/Epoch (s)	Inference Time (ms/sample)
CNN	4.8	12.4	2.1
BiLSTM	6.2	18.6	3.4
BERT	110	96.8	12.7
Proposed FNN	8.5	22.3	3.9

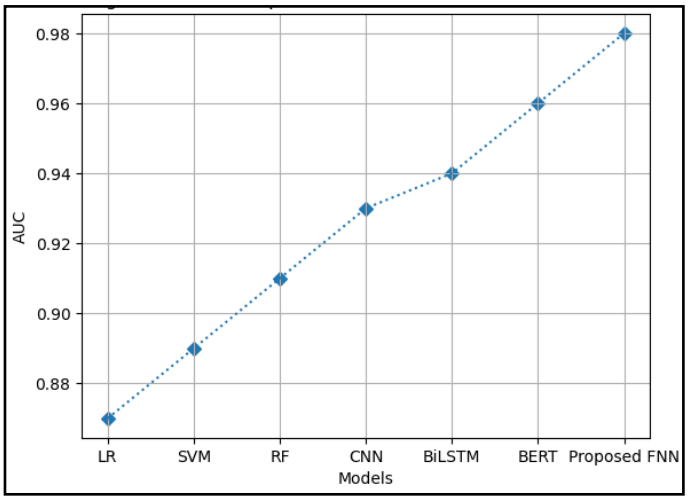


Figure 6
AUC Comparison of Fake News Detection Models

6. Conclusions

This study introduced an Intelligent Fuzzy Neural Network designed for dependable and interpretable fake news detection in digital media environments. The proposed three-layer framework combines fuzzy reasoning with neural network learning to manage uncertainty, vague language, and diverse feature types effectively. Experimental evaluation shows that the model surpasses traditional machine learning and deep learning methods across key metrics such as accuracy, F1-score, and AUC, while simultaneously delivering clear rule-based justifications for its predictions. The findings highlight that integrating lexical, semantic, and credibility-related attributes within a fuzzy–neural structure improves both reliability and transparency. Consequently, the approach provides a credible solution for practical misinformation surveillance applications. Future research will extend the model to multilingual scenarios, enhance resistance to adversarial manipulation, and support real-time operational deployment.

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Received December, 2025