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ORIGINAL ARTICLE

FuDL-SM: A Hybrid Fuzzy Deep Learning Framework for Sentiment Analysis of Zoological and Wild Life Conservation based Social Media Data

Dr A Angelpreethi[1]*, P Anitha[2], R Sivagami[2]

1 Department of Computer Science, St Joseph's College (Autonomous), Affiliated with Bharathidasan University, Tiruchirappalli -620002, Tamil Nadu, India
2 Department of Computer Science, Dr. Umayal Ramanathan College for Women, Karaikudi, Tamil Nadu, India

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* **Corresponding author**.

angelpreethi.mca@gmail.com; angelpreethi_cs1@mail.sjctni.edu

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Abstract

Background: As microblogging becomes more popular, users produce vast amounts of text expressing different feelings and opinions. Twitter, in particular, attracts millions of users who share brief and informal messages. Sentiment analysis of such posts continues to be a difficult task because of informal language, sarcasm, abbreviations, and ambiguity. **Objectives:** This study desire to create a new system called FuDL-SM that combines fuzzy logic and deep learning. The goal is to better understand user opinions on Twitter by improving the accuracy of sentiment analysis, especially when dealing with unclear or uncertain expressions in the reviews. **Methods:** The FuDL_SM model uses deep learning model along with fuzzy membership functions and GloVe word embedding to capture both the meaning of text and the uncertainty in sentiment. **Findings:** The model was tested on 51,757 wild life reviews which were cleaned and labeled using the VADER sentiment tool. Proposed method achieved 94.28% accuracy, 93.85% precision, 94.12% recall, and 94.03% F1-score, which are better than existing systems. The use of fuzzy logic helped improve accuracy by 10% and made the system better at handling uncertain or mixed sentiments. **Novelty**: Unlike other methods that use fuzzy logic inside the network layers, this model applies fuzzy inference after the deep learning classification step. This final step helps refine the sentiment predictions and makes the model more dependable.

Keywords: FuDL SM; Glove Embedding; Deep Neural Networks; Fuzzy inference system; Wild life conservation; Zoological data

1 Introduction

With the fast development of social media platforms such as Facebook, Instagram, and Twitter, there has been a major increase in user-generated content that expresses the thoughts and opinions of the general public on various topics [1], [2]. Sentiment Analysis (SA), also known as opinion mining, has become an essential sub field of Natural

Language Processing (NLP) to analyze these opinions for decision making in business, social studies and marketing.[2],[3].

However, analysing short and informal texts especially from Twitter, remains challenging due to noisy and unstructured nature[4]. Existing algorithms such as Naïve Bayes and Support Vector Machines (SVM) depend on manually constructed features, which often fail to capture semantic relationships in text[2],[5]. Deep neural networks like CNN, LSTM, and BiLSTM do better than traditional methods by automatically finding complex relationships between words and meanings.[4],[6],[7]. However, these models still struggle with uncertain, sarcastic and mixed sentiment texts with unclear polarity[3],[8]. Uncertainty in sentiment analysis refers to situations where a review does not express a clear positive, negative or neutral emotion which may mislead the classifier.

Several studies have explored opinion mining using different machine learning, deep learning, and fuzzy-based models[4],[5],[8],[9]. A comparative summary of the recent literature is presented in Table 1, highlighting their methodologies, datasets and its limitations.

Table 1. Overview of existing works

Reference	Methods Used	Key Features	Dataset	Novelty
[4]	Single-Layer BiLSTM	This study offers the lightweight Deep Learning model and global pooling	MR, SST2, IMDb	Similar to complex models but uses less computation
[5]	ABC + BoW + Naïve Bayes + KNN + ATO-DRNN	Uses ABC for feature optimization; fuzzy rule-based scoring	Twitter Dataset	Combines fuzzy and deep learning; high accuracy; not great at dealing with uncertainty
[8]	Hybrid Fuzzy Model + SVM	Uses dense and sparse vectors; automatically adjusts hyper parameters	SemEval 2017	Fuzzy text classifier that doesn't need manual adjustments
[10]	Fuzzy Deep Hybrid	combination of Fuzzy logic and BiLSTM	Arabic Datasets	Deals with unclear language in Arabic text reviews
[11]	Ensemble Learning based on Fuzzy logic	Uses Random Forest, Gradient Boosting, LSTM with fuzzy logic	Social Media Dataset	Takes care of ambiguity; better accuracy, precision, recall, and F1-score[12]
[13]	Fuzzy HCN-Net (Hierarchical CNN)	Combines BERT, ATE, TF-IDF, and word2vec with fuzzy deep hybrid approach	Text Reviews	Has better accuracy and F1-score; good at handling unclear meanings

Recent studies have also investigated CNN, LSTM, Fuzzy based learning and multimodal SA combining textual and visual cues[7],[14]. However, this integration makes it difficult to adjust predictions after classification and still fails to handle uncertain sentiment reviews. Also failed to handle uncertain sentiment reviews. Most current approaches aim for higher accuracy but pay limited attention to interpretability.

To overcome these limitations, this study proposes a hybrid deep learning model (FuDL_SM) that integrates Fuzzy logic with deep learning networks for increasing the classification accuracy[5],[10]. This fuzzy logic assigns the membership values to each sentiment, and classifies sentiments into strictly positive, moderately positive, neutral, moderately negative and strictly negative categories. Unlike conventional models that make fixed decisions, the proposed method provides a more nuanced and human-like sentiment prediction. This deep learning and fuzzy integration improve classification accuracy, enhances interpretability and helps users make reliable predictions based on sentiment outcomes.

The major contributions of this study are as follows:

1. Hybrid framework – A novel fuzzy deep learning architecture that combines fuzzy membership functions with the BiLSTM network for robust sentiment classification and handling uncertainty[5].
2. Comprehensive Evaluation- The proposed work compares FuDL-SM against the deep learning model (BiLSTM) and the proposed hybrid model using benchmark Twitter datasets[11],[13],[6].
3. Improved Performance- Experimental results demonstrate that the present study attains improved accuracy, precision, recall, and F-Score compared to existing approaches.

2 Methodology

The proposed FuDL_SM approach combines the VADER based sentiment Labeling, GloVe embedding, Bidirectional LSTM and fuzzy logic based classification for robust SA of Wild life conservation- related tweets [13], [6].

Phase I: Gathering and Preparing Data

2.1 Data Collection:

The dataset used in this study was sourced from publicly available Twitter platforms and a Kaggle repository containing 51,757 unique tweets and retweets related to wildlife conservation, zoological biodiversity, endangered animal species, habitat preservation and ecological awarness [7]. Approximately 73% of the records correspond to user tweets, 22% to retweets, and the remaining 5% (2,986 entries) to miscellaneous tweet types [7] . The dataset was downloaded and stored in CSV format for pre-processing. The attributes of the CSV includes Tweet timestamp, Content, type of tweet, retweets, likes, number of followers etc. This study focuses only on text based review for further processing.

2.2 Data preparation:

Data cleaning was conducted to refine the raw corpus and prepare it for model training. Figure 1 clearly presents the necessary pre-processing steps. The textual normalization included case folding, elimination of hashtags, punctuation, URLs, stop words, numerical values, and application of stemming [15], [16]. These steps ensured that the dataset was free from redundant information, making it suitable for further processing.

Phase II: Feature Extraction

2.3 VADER based Sentiment Labelling:

Due to the absence of pre-assigned sentiment categories in the dataset, the study used VADER sentiment tool provided in NLTK library was adopted for automatic annotation [1]. For each cleaned tweet t_i is assigned with, three polarity scores. The overall compound value $C_i \varepsilon$ [-1,1] determined its sentiment polarity [1].

$$Sentiment\, t_i = \begin{cases} Positive, & if\, C_i > 0.05 \\ Negative, & if\, C_i < -0.05 \\ Neutral, & otherwise \end{cases}$$

This process automatically labeled all 51,757 entries. The distribution was 21,221 positive tweets; 18,633 neutral tweets and 11,903 tweets are negative after processing.

2.4 Word Embedding using GloVe

The VADER-labeled corpus was subsequently converted into numerical vectors using 100-dimensional pre-trained GloVe embedding to capture semantic relationships among words [17], [18]. This embedding was used to capture statistical information and sentiment relationships globally [19].

Phase III: Sentiment Estimation using Neural Network and Fuzzy Logic

2.5 Hybrid Fuzzy- Deep Sentiment Classification

Once weighted embedding were generated, a Bidirectional LSTM was trained to learn contextual dependencies in both forward and backward directions. [4], [6], [20]. The LSTM layer is responsible for managing and storing the data over long-term sequences, the dropout layer is used to prevent overgeneralization [14]. The output dense layer applied a Softmax activation to produce sentiment probability scores. LSTM based architectures have recently gained attention for effective sentiment classification [12].

Proposed Algorithm:

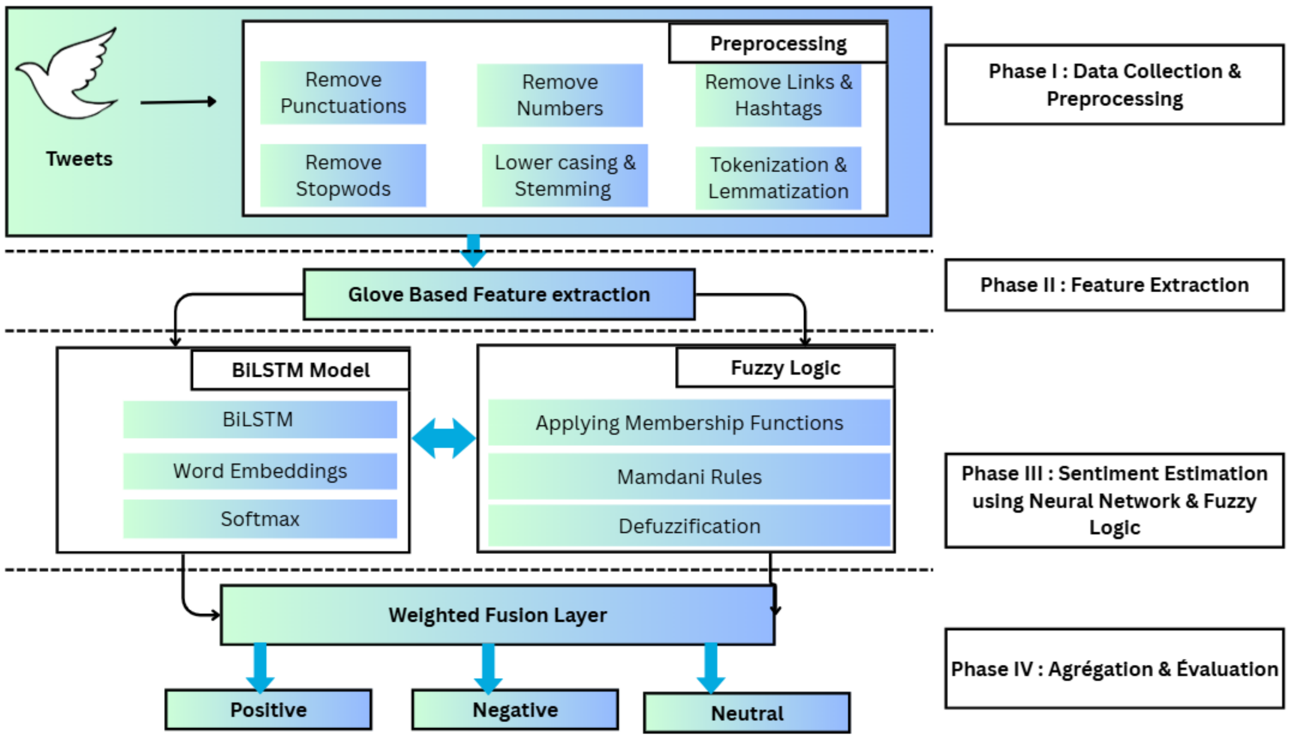

Fig 1. Methodology of the proposed FuDL_SM approach

Algorithm: FuDL-SM
Input:
A set of tweets T={t_1,t_2,t_3.....t_n}
Pre-trained Glove embedding E
Fuzzy Membership functions $\mu_{POS}\ (x), \mu_{Neu}\ \ (x),\ \mu_{Neg}(x)$
Fuzzy Rule base R= { R_1,R_2....R_{10}}
Output
Final sentiment labels $S_i \in$ {Positive, Neutral, Negative}
// Data Collection and Pre-processing
Step 1: Collect tweets T using hashtags and keywords.
Step 2: Pre-process each tweet t_i by:
Lowercasing, removing stop words, punctuation, links, Hashtags
Tokenizing into words $w_{i,j}$
Step 3: VADER based sentiment labelling &
Convert tokens into vectors using Glove
$V_{i,j}$ =E($w_{i,j}$)
// sentiment Estimation using Neural Network
Step 4: For each t_i pass {$v_{i,j}$} through BiLSTM / LSTM to obtain softmax output:
Pi ={p_{pos}, p_{neu}, p_{neg} }, $p_{pos} + p_{neu} + p_{neg} = 1$
// Fuzzification
Step 5: Calculate fuzzy membership values corresponding to the positive, neutral and negative probability outputs

$$\mu_{POS}\ (p_{pos}), \mu_{PNEU}\ (p_{neu}), \mu_{NEG}\ (p_{neg})$$

//Evaluating the Rules

Step 6: For each Rule R_k compute the activation strength
α_k = min (antecedent memberships)
// Aggregation
Step 7: Aggregate the output for each sentiment class

$$\mu*_{POS}\ (y) = \max\min(\alpha_k, \mu_{POS}\ (y))\ \ for\ all\ k \in POS$$

$$\mu*_{NEU}\ (y) = \max\min(\alpha_k, \mu_{NEU}\ (y))\ \ for\ all\ k \in NEU$$

$$\mu*_{NEG}\ (y) = \max\min(\alpha_k, \mu_{NEG}\ (y))\ \ for\ all\ k \in NEG$$

// Defuzzification
Step 8: Compute final crisp sentiment score using centroid method:

$$S_i = \frac{\int_{-1}^{1} y.\max\left(\mu*_{POS}\ (y), \mu*_{NEU}\ (y), \mu*_{NEG}\ (y)\right) dy}{\int_{-1}^{1} \max\left(\mu*_{POS}\ (y), \mu*_{NEU}\ (y), \mu*_{NEG}\ (y)\right) dy}$$

// Decsion-making
Step 9: classify sentiment $S_i = \begin{cases} Positive, & S_i > \theta_p \\ Neutral & |S_i| > \theta_n \\ Negative & S_i > -\theta_p \end{cases}$
$Where\ \theta_p\ ,\ \theta_n\ are\ predefined\ thresholds.$

2.6 Fuzzy based classification

After the BiLSTM based classification, each review is represented by a three-dimensional probability vector which consists of positive, negative and neutral values[6]. Rather than selecting the sentiment class with the highest probability, a fuzzy inference process is employed to manage ambiguity and uncertainty inherent in textual sentiments. This fuzzy logic effectively handles the uncertainty and ambiguity in the sentiment classification process. The probabilistic score (P) obtained from the deep learning models is given as an input to the fuzzy based classification phase[5],[10],[11].

The probability vector is defined as

$$P = \left\{ P_{pos}, P_{neu}, P_{neg} \right\} \tag{1}$$

The **Eq (1)** describes the set of probabilistic score and its three values.

$$P_{pos} = Probability\ that\ the\ input\ text\ review\ is\ positive$$

$$P_{neu} = \ Probability\ that\ the\ input\ text\ review\ is\ neutral$$

$$P_{neg} = \ Probability\ that\ the\ input\ text\ review\ is\ negative$$

Since the above three values are outputs of the Softmax they must[?]

Satisfy

$$P_{pos} + P_{neu} + \ P_{neg} = 1 \tag{2}$$

Each probability is assigned through predefined membership functions namely Triangular membership, Trapezoidal membership and Gaussian membership[9].

2.6.1. Positive Sentiment:

The Gaussian membership function was chosen for modeling positive sentiment, as it represents smooth progressive variations associated with increasing positivity. Its bell-shaped curve naturally models smoothly increases and decreases around strong positivity.

$$\mu_{POS}(x) = e^{-\frac{(x-0.8)^2}{2(0.1)^2}} \tag{3}$$

The Gaussian membership value for positive sentiment is taken as x=0.8, which represents the peak of strongest positivity. As the value moves away from 0.8, the positivity gradually decreases. This makes the Gaussian membership function a good choice.

2.6.2. Negative Sentiment:

A triangular membership function was employed for negative sentiment since it effectively captures abrupt changes associated with strong negative expressions. The sentiment is very strongly negative at very low probability values, but as the probability goes up, the intensity of the negativity decreases rapidly until it is zero. Membership values are represented in **Equation 4**.

$$\mu_{NEG}(x) = \begin{cases} 1 & 0 \le x \le 0.2 \\ \frac{0.4-x}{0.4-0.2} & 0.2 < x < 0.4 \\ 0 & x \ge 0.4 \end{cases} \tag{4}$$

The maximum negativity is assumed at 0.2 here and the opinion is the most negative. Beyond this point the negativity rapidly diminishes and disappears at x=0.4 making the triangular form suitable for modeling negative intensity.

2.6.3. Neutral Sentiment:

The trapezoidal membership is used for neutral sentiment because it tends to have a wider, stable range. In between the middle values (approximately 0.4 to 0.6), the sentiment is entirely neutral and the sloping sides reflect the progressive changes towards either negative or positive domains. **Eq (5)** represents the Trapezoidal membership values.

$$\mu_{NEU}(x) = \begin{cases} 0 & x \le 0.3 \\ \frac{x-0.3}{0.4-0.3} & 0.3 < x \le 0.4 \\ 1 & 0.4 < x \le 0.6 \\ \frac{0.7-x}{0.7-0.6} & 0.6 < x \le 0.7 \\ 0 & x \ge 0.7 \end{cases} \tag{5}$$

In this model, the strongest neutrality is between x=0.4 and x=0.6 and a smooth transition on each side to cover borderline cases[9],[21].

2.7 Fuzzy Rule base and Inference:

At the final phase of the FuDL-SM architecture, a Mamdani-style fuzzy logic inference system is developed to narrow down the sentiment prediction of the BiLSTM model[17],[19].

The three probability values $P = \{P_{pos}, P_{neu}, P_{neg}\}$ where $P_{pos} + P_{neu} + P_{neg} = 1$

These values are converted to fuzzy sets using the existing membership functions: Gaussian, Trapezoidal and Triangular: Positive, Neutral and Negative respectively. Such rules encode intuitive linguistic information that is consistent with human judgment. The fuzzy inference procedure is based on the typical *min-max* composition. The antecedent component of every rule is processed in the usage of the minimum operator, and the output is combined using the maximum operator. The fuzzy sets (Positive, Neutral, Negative), which are obtained, are then fused into one output. Lastly, we use the Centroid Defuzzification technique to generate a sharp sentiment score, S$\in [-1,1]$[22]. In which negative values reflect Negative sentiment, values close to zero reflect Neutral sentiment and positive values reflect Positive sentiment.

2.7.1. Fuzzy Rules:

The fuzzy rule base in the FuDL-SM architecture consists of ten rules that model the interactions between the sentiment probabilities p_{pos}, p_{neu}, $p_{neg.}$ Each of the rules uses the minimum as well as maximum operators. Minimum operator is used to compute activation strength, and the maximum is used to aggregate the values. The detailed rules are presented in Table 2.

Table 2. Fuzzy Rule Base for FuDL_SM [16]

Rule ID	Ppos	Pneg	Pneg	Sentiment
R1	HIGH	-	LOW	POSITIVE
R2	HIGH	LOW	-	POSITIVE
R3	-	HIGH	LOW	POSITIVE
R4	LOW	HIGH	-	NEGATIVE
R5	LOW	LOW	MEDIUM	NEUTRAL
R6	HIGH	HIGH	-	NEUTRAL
R7	HIGH	-	MEDIUM	SLIGHTLY POSITIVE
R8	-	HIGH	MEDIUM	SLIGHTLY NEGATIVE
R9	LOW	LOW	HIGH	NEUTRAL
R10	LOW	HIGH	LOW	NEGATIVE

Table 2 shows the fuzzy rules used for sentiment classification in the proposed system. In the table columns Ppos, Pneg, Pneu represents the sentiment probabilities obtained from the LSTM-based model after applying the SoftMax Function. These values are mapped using its membership functions. The high, medium, low represents the degrees of membership in the fuzzy sets. The hyphen (-) in the table indicates that the rule does not depend on the specific probability.

Phase IV: Aggregation & Evaluation

3 Results and Discussions

The FuDL-SM (Fuzzy Deep Learning Sentiment Model) was tested on a standard Twitter wild life conservation dataset to check how well it handles uncertainty and unclear messages that are common in social media. The model's performance was measured using usual measures like accuracy, precision, recall, and F1-score [12]. The obtained results are compared with the existing state-of-the-art approaches from the literature to establish the significance and novelty of the proposed method [23].

3.1 Performance Evaluation of the proposed model:

The FuDL-SM framework integrates BiLSTM with GloVe embedding and a fuzzy inference layer applied at the post-classification stage. This integration improves the deep learning outputs by resolving uncertainty in sentiment prediction. Table 3 presents the outcomes obtained after applying the data pre-processing steps.

Table 3. Outcomes from the data cleaning phase

Pre-Processing Step	Before Cleaning	After Cleaning
Number of tweets	51,757	51,757
Average Length	26	15
Tweets with URL's	18,925	-
Tweets with Hashtags	21,680	-
Tweets with Mentions	17,012	-
Total Stop Words Removal	-	7,85,000
Vocabulary Size (Unique Terms)	34,210	10,472

FuDL-SM achieved 94.28% accuracy, 93.85% precision, 94.12% recall, and an F1-score of 94.03% [12]. The high and balanced performance values demonstrate that the FuDL-SM framework effectively handles the irregularities of social media language while maintaining interpretability through fuzzy reasoning.

The experimental results demonstrate that adding fuzzy rules to the post-classification phase greatly improves the BiLSTM model's classification effectiveness. Earlier models often misinterpreted unclear sentiments due to their dependence on fixed probability thresholds. In comparison, the fuzzy reasoning part of FuDL-SM is good at identifying uncertain opinions by using words like slightly negative or moderately positive [24].

3.2 Comparative Analysis with Existing Approaches

Earlier work on domain-specific weighting approaches also demonstrated similar interpretability improvements [12]. The FuDL-SM model was tested against several recent advanced sentiment analysis techniques to compare how well it performs. These include the single layer LSTM proposed by Zabit Hameed [4], Sireesha and Raj Kumar [5], Alzaid and Fkih [8], Fuzzy ensemble model by Nandi et al. [11], and Fuzzy HCN Net by Thakur et al. [13], the LSTM model developed by Mollah [21].

Table 4. Comparative outcomes of opinion mining models [12]

Author	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Zabit Hameed & Garcia-Zapirain [4]	85.7	85.8	85.6	90.5
Sireesha & Raj Kumar [5]	89..7	93.7	91.7	92.0
Alzaid & Fkih [8]	63.7	63.2	63.2	64.6
Nandi et al. [11]	88.6	89.2	88.9	89.0
Thakur et al. [13]	90.4	90.6	90.4	91.5
Mollah [21]	67.8	68.0	67.9	68
Proposed FuDL-SM	93.85	94.12	94.03	94.28

The results show that FuDL-SM beats other models in every metrics. Compared with Thakur et al. [13], FuDL-SM achieves a 3.63% higher accuracy and 3.63% higher F1-score while maintaining lower computational overhead. Although LSTM [21] and BiLSTM [4] models work well, they struggle when dealing with unclear or mixed emotions in text. Methods that use fuzzy ensembles or layered CNN structures improve the ability to understand results, but they also require more computing power [11]. FuDL-SM maintains equilibrium among precision, interpretability, and computational cost [24].

3.3 Discussion on Novelty and Contribution

The new part of this study is using fuzzy logic after the classification step in the BiLSTM model, instead of including fuzzy logic directly in the network layers. Because of this, the framework is better at dealing with tweets that show mixed or unclear feelings.

GloVe embedding model has proven highly effective. To show its power, the proposed model is tested with other models such as One-Hot Encoding, Random Embedding, Word2Vec Embedding and GloVe Embedding. The results are reported in the order of Accuracy, Precision, Recall, and F1-score [12]. The One-Hot encoding method achieves 78.42%, 76.85%, 77.12%, 76.98 % [12]. The random Embedding method achieves moderate improvement, attaining 82.56%, 80.24%, 81.05% and 80.64%. Further improvement was observed with Word2vec embedding which achieves 88.37%, 87.54%, 87.92%, 87.73%. Notably the glove embedding (FuDL_SM) method outperformed all other approaches, which achieves highest values of **94.28%**, **93.85%**, **94.12%**, and **94.03%** [24].

Figure 2 compares the model's accuracy, precision, recall, and F1-score before and after using fuzzy reasoning to further highlight the performance improvement made possible by fuzzy integration. After fuzzy integration, the results clearly indicate a substantial improvement across all measures, supporting the effectiveness of the proposed FuDL-SM model in sentiment analysis tasks.

3.4 Computational efficiency analysis

The time complexity of the models is evaluated. BiLSTM model requires slightly higher training time (**160s**) compared to the LSTM (**140s**) due to its bidirectional processing of input sequences [4], [5]. Similarly, test time also increases marginally from **48s** to **50s**. While BiLSTM incurs higher computational cost, the performance gains in terms of accuracy and F1-score justify the additional overhead. After Fuzzy integration, the performance improves to an overall accuracy [5], [8], [10].

Furthermore, the FuDL-SM model maintains computational efficiency which is presented in Figure 3. This demonstrates that the model achieves higher accuracy without significant time overhead, making it feasible for real-time applications [18].

While earlier models such as LSTM and BiLSTM demonstrated good performance, their accuracy was limited to **81.4%** and **83.6%**, respectively [4], [21]. The CNN-LSTM hybrid model proposed achieved improved results with an accuracy of **85.0%** but still lacked in handling semantic ambiguity effectively [22], [18].

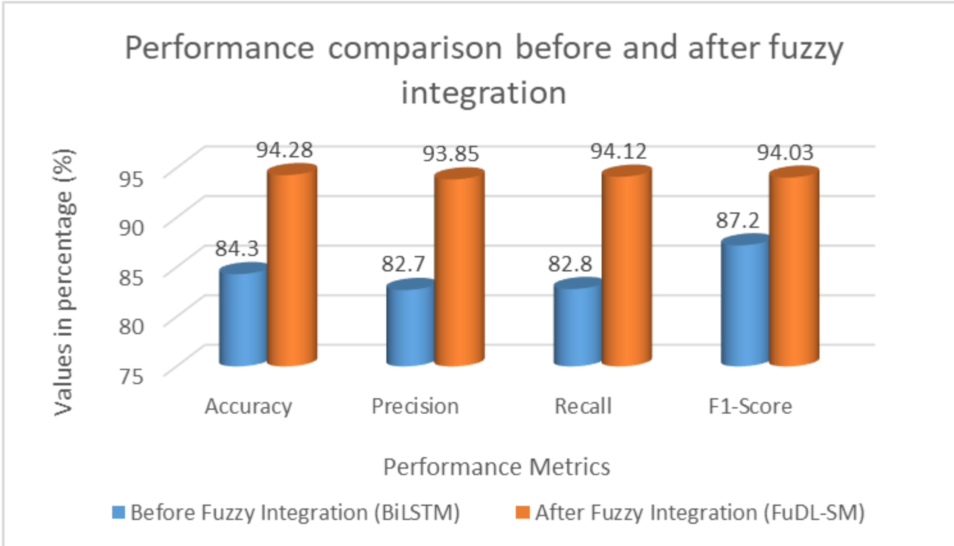

Fig 2. Performance comparison before and after fuzzy integration

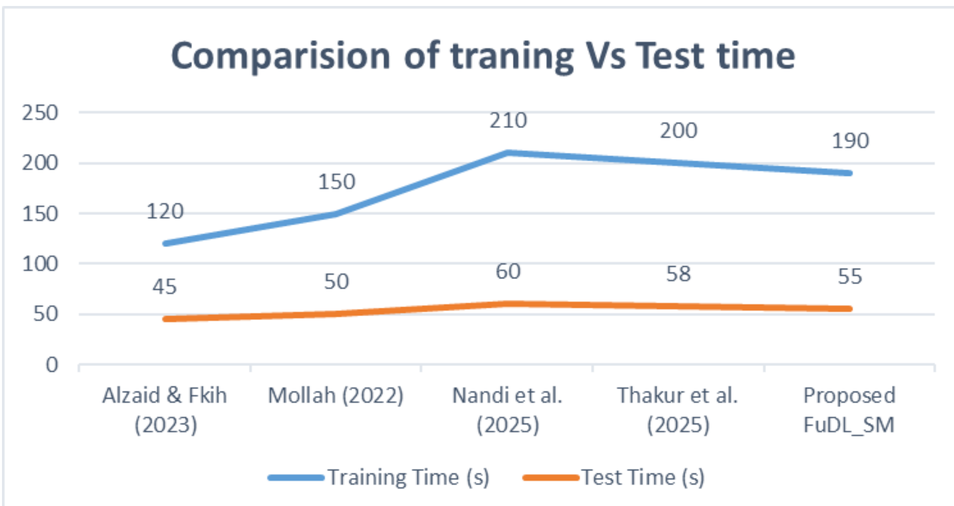

Fig 3. Comparison of training time vs testing time

4 Conclusion

This FuDL_SM integrates fuzzy reasoning and deep learning to enhance sentiment prediction accuracy on wild life and ecological awareness data contributing to digital conservation studies. This system showcases strong ability to handle uncertainty and ambiguous user expressions without sacrificing predictive accuracy. The outcomes suggest that FuDL-SM achieves better performance when compared to other benchmark models.

The study demonstrated that BiLSTM captures sequence patterns more effectively, while fuzzy logic helps in handling uncertainty in conservation related discussions. Meanwhile, GloVe embedding improved the semantic understanding of the text, giving the model a stronger foundation for classification. Together, these components made the framework more resilient and reliable for analyzing real-world zoological and ecological social media data.

5 Future Directions

While the results are promising, there are still areas that can be explored further. In the future, we plan to:

1. Expand the framework to support multiple languages, enabling sentiment analysis across various social media platforms.
2. Investigate aspect-based sentiment analysis with focus on detailed opinions regarding specific features of a conservation initiative or policy discussion.
3. Test the system on larger and more diverse datasets, including multimodal inputs such as text alongside images or videos.

These directions will make the framework more scalable, adaptable, and useful for both academic research and industrial applications.

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