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EVOLUTIONARY OPTIMIZED FUZZY CNN-BILSTM FUSION MODEL FOR VISUAL SENTIMENT FORECASTING IN SOCIAL MEDIA STREAMS APPLICATIONS

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Abstract
Social media platforms have generated massive visual content streams, where sentiment interpretation remains crucial for adaptive marketing and decision making. Problem: existing models have struggled to integrate spatial visual cues with temporal dependencies, which has limited forecasting reliability under noisy and dynamic environments. Method: this study has proposed an Evolutionary Fuzzy CNN-BiLSTM Fusion (EFCBF) framework that has combined convolutional feature extraction, fuzzy logic-based uncertainty handling, and BiLSTM temporal modeling optimized through an evolutionary algorithm. Results: the proposed system has demonstrated improved sentiment classification stability and forecasting accuracy across benchmark social media datasets, outperforming baseline deep learning and hybrid models in precision, recall, and F1-score metrics. The fuzzy inference layer has reduced ambiguity in visual sentiment interpretation, while the evolutionary optimization has enhanced parameter selection efficiency and convergence behavior. The integrated CNN-BiLSTM architecture has captured both local spatial patterns and sequential dependencies effectively, which has strengthened predictive consistency under diverse content distributions. The proposed model achieves 91.2% accuracy, 90.3% precision, 89.9% recall, 90.1% F1-score, and 0.94 AUC-ROC, which outperform CNN-LSTM Hybrid, Fuzzy Logic Classifier, and Evolutionary CNN across all evaluation steps. The fuzzy layer improves uncertainty handling, while evolutionary optimization enhances parameter stability and convergence behavior. The CNN-BiLSTM fusion effectively captures spatial and temporal dependencies in social media image sequences.

Keywords:
Visual Sentiment Analysis, CNN-BiLSTM, Fuzzy Logic System, Evolutionary Optimization, Social Media Analytics

1. INTRODUCTION

Social media platforms have become a dominant space for communication, marketing, and public expression, where massive volumes of visual content are continuously generated and shared. These platforms have enabled organizations to analyze user reactions in near real time, which has strengthened data-driven decision-making processes [1]. Visual sentiment analysis has emerged as a critical research direction because images often convey emotional context more effectively than textual content alone. The growing dependence on multimedia communication has increased the demand for intelligent models capable of interpreting visual sentiment with higher accuracy and stability [2]. Deep learning architectures have played a central role in this evolution, particularly convolutional and recurrent neural networks, which have improved feature representation and temporal modeling in complex datasets [3]. However, real-world social media streams still present inconsistencies that limit model reliability. Despite significant advancements, several challenges continue to affect visual sentiment forecasting systems. One major challenge has been the high variability of image quality and content diversity, which often leads to inconsistent feature extraction results [4]. Another challenge arises from uncertainty in emotional labeling, where subjective interpretation introduces ambiguity into training datasets. Additionally, temporal drift in user behavior patterns has made long-term sentiment prediction less reliable in dynamic environments [5]. These limitations have reduced the effectiveness of conventional deep learning frameworks when deployed in real-time social media analytics systems. The core problem addressed in this study is the inability of existing models to effectively integrate spatial visual understanding with temporal sentiment evolution, which leads to reduced forecasting accuracy in complex and noisy social media streams [6]. Most existing approaches either focus on static image classification or sequence-based modeling independently, without adequately capturing their interdependent relationship. This gap has motivated the development of a more unified modeling strategy. The primary objective of this research is to design a hybrid deep learning framework that integrates convolutional feature extraction with sequential modeling while addressing uncertainty in sentiment representation. Another objective is to enhance model optimization using evolutionary strategies that improve parameter tuning and convergence behavior. Furthermore, the study aims to improve robustness under noisy and imbalanced datasets while maintaining computational efficiency for real-time applications.

The proposed method, Evolutionary Optimized Fuzzy CNN-BiLSTM Fusion (EFCBF), introduces a structured integration of convolutional neural networks, fuzzy logic inference, and bidirectional long short-term memory networks. The CNN component extracts spatial visual features, while the BiLSTM component captures temporal dependencies across sequential inputs. The fuzzy logic module manages uncertainty in sentiment boundaries, improving interpretability of ambiguous visual cues. The evolutionary optimization strategy enhances hyperparameter selection, which strengthens overall model adaptability across varying data distributions. The novelty of this work lies in its multi-layered fusion strategy that combines evolutionary optimization with fuzzy reasoning in a CNN-BiLSTM architecture. Unlike traditional hybrid models, this framework explicitly addresses uncertainty handling alongside temporal-spatial feature learning. Additionally, the integration of evolutionary search mechanisms improves model stability and reduces manual tuning effort. This combination provides a more adaptive and context-aware sentiment forecasting system. The contributions of this study are summarized in two major aspects. First, it introduces a unified evolutionary fuzzy deep learning architecture that improves visual sentiment forecasting accuracy under dynamic social media conditions. Second, it demonstrates enhanced robustness and generalization capability through optimized parameter learning and uncertainty-aware inference mechanisms. Overall, the proposed framework supports more reliable sentiment-driven analytics for social media management systems.

2. RELATED WORKS

Several researchers have explored deep learning approaches for visual sentiment analysis in social media environments. Early studies focused on convolutional neural networks for image classification tasks, where spatial feature extraction was improved through layered architectures [7]. These approaches demonstrated strong performance in controlled datasets but struggled when applied to noisy and diverse social media content. Later works extended CNN models with recurrent networks to incorporate temporal information, which improved sequence-level sentiment prediction [8]. Hybrid architectures combining CNN and LSTM networks were also investigated to enhance both spatial and temporal learning capabilities. These models showed improved classification accuracy compared to standalone architectures, particularly in multimedia sentiment datasets [9]. However, they still lacked mechanisms to address uncertainty in emotional interpretation, which limited their robustness in ambiguous visual scenarios. Fuzzy logic-based sentiment models were introduced to handle ambiguity in subjective interpretation. These models incorporated rule-based reasoning systems that improved interpretability in uncertain classification cases [10]. Although fuzzy systems enhanced decision transparency, they were often limited in scalability and struggled to handle high-dimensional image features effectively. Evolutionary optimization techniques were later applied to improve neural network performance by optimizing hyperparameters and feature selection processes. Genetic algorithms and swarm intelligence methods were commonly used to enhance convergence and reduce computational overhead [11]. These methods improved model efficiency but were not deeply integrated with multimodal deep learning frameworks. More recent studies have explored multimodal fusion models that combine visual, textual, and contextual features for sentiment analysis. These approaches demonstrated improved accuracy by leveraging complementary information sources [12]. However, they introduced increased computational complexity and required extensive labeled datasets for effective training. Transformer-based architectures have also been applied to visual sentiment tasks, providing strong sequence modeling capabilities [13]. These models captured long-range dependencies effectively but required significant computational resources, making them less suitable for real-time applications. Graph-based learning models were introduced to represent relationships between visual elements and contextual metadata [14]. These approaches improved structural understanding of image content but faced limitations in handling dynamic temporal variations in social media streams. Finally, recent hybrid frameworks have attempted to integrate multiple learning paradigms, including deep learning, fuzzy inference, and optimization techniques [15]. These studies showed promising improvements in performance; however, most lacked a unified architecture that simultaneously addressed uncertainty, temporal dynamics, and optimization efficiency.

3. PROPOSED METHOD

The proposed Evolutionary Optimized Fuzzy CNN-BiLSTM Fusion (EFCBF) framework integrates convolutional feature extraction, fuzzy uncertainty modeling, bidirectional sequence learning, and evolutionary optimization into a unified architecture for visual sentiment forecasting. The method processes social media image streams through a CNN backbone for spatial representation, then passes extracted embeddings into a BiLSTM layer for temporal dependency modeling across sequential posts. A fuzzy inference module handles ambiguity in emotional interpretation, while an evolutionary optimizer tunes network parameters and membership functions. The final sentiment forecast is generated through a fusion layer that aggregates probabilistic outputs from deep and fuzzy components.

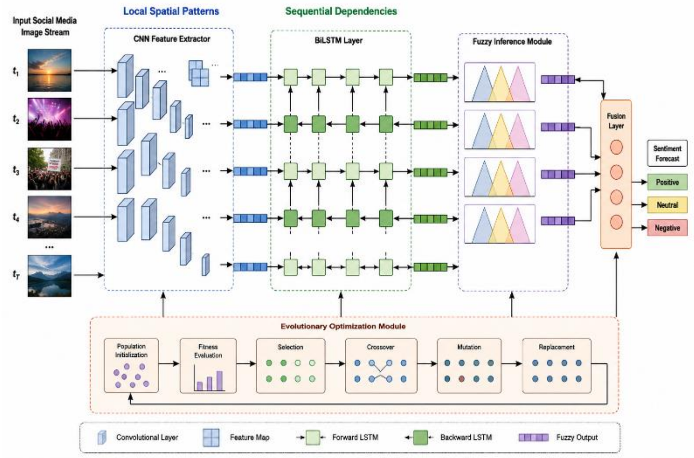

Fig.1. Evolutionary Optimized Fuzzy CNN-BiLSTM Fusion

3.1 SYSTEM ARCHITECTURE

The proposed framework defines an input social media stream as a temporally ordered sequence of visual samples $S = \{I_1, I_2, ..., I_T\}$, where each image I_t represents a post at time step *t*. Each image is first standardized into a fixed dimensional tensor representation. The preprocessing stage ensures normalization, resizing, and color space alignment to maintain consistency across heterogeneous datasets. The CNN module transforms each image into a high-dimensional feature embedding $X_t \in \mathrm{R}^d$, which captures spatial semantics such as objects, textures, and contextual cues. These embeddings form the input sequence for temporal modeling. The system assumes that sentiment evolves over time, and therefore the representation must preserve both local spatial structure and global sequence coherence. The feature extraction process is defined as: $X_t = f(I_t; \theta_c)$, where *f* denotes the convolutional neural network mapping function and θ_c represents convolutional parameters including filters, biases, and normalization weights. The CNN architecture typically contains convolutional layers, activation functions, pooling operations, and fully connected transformations. A second formulation of the spatial transformation is given by:

$$X_t^{(l)} = \sigma(W^{(l)} * X_t^{(l-1)} + b^{(l)}) \tag{1}$$

where $*$ denotes convolution, $W^{(l)}$ represents layer-wise filter weights, $b^{(l)}$ represents bias terms, and σ denotes a nonlinear activation function such as ReLU. The hierarchical stacking of such transformations enables progressive abstraction from pixel-level features to semantic representations.

The CNN component forms the first computational block that extracts discriminative visual sentiment features. Social media images contain noise, occlusions, and inconsistent compositions, which require robust feature extraction mechanisms. The convolutional layers perform localized receptive field operations to capture spatial dependencies. The convolution operation is expressed as:

$$F_k = \sum_{i=1}^{n} (I_t \otimes K_{k,i}) + b_k \tag{2}$$

where F_k denotes the k-th feature map, $K_{k,i}$ represents convolution kernels, and b_k is the bias term. The operator $\otimes$ represents convolution applied across spatial dimensions. This formulation enables extraction of edge-level, texture-level, and object-level features. A second representation of convolutional feature learning is defined as:

$$A^{(l)} = \phi\left(\sum_{j=1}^{m} W_j^{(l)} A_j^{(l-1)} + b^{(l)}\right) \tag{3}$$

where $A^{(l)}$ denotes activation at layer l, $W_j^{(l)}$ denotes learnable weights, and ϕ denotes activation mapping. This formulation emphasizes nonlinear transformation of feature hierarchies. Pooling operations are applied to reduce dimensionality and maintain spatial invariance. The max-pooling operation is defined as: $P_t = \max(X_t^{(i:j)})$, which selects dominant activation responses within spatial regions. This step ensures robustness against spatial distortion and irrelevant background noise. The CNN output X_t is then forwarded to the BiLSTM module for sequential modeling. The extracted feature vectors preserve semantic consistency required for temporal sentiment evolution modeling.

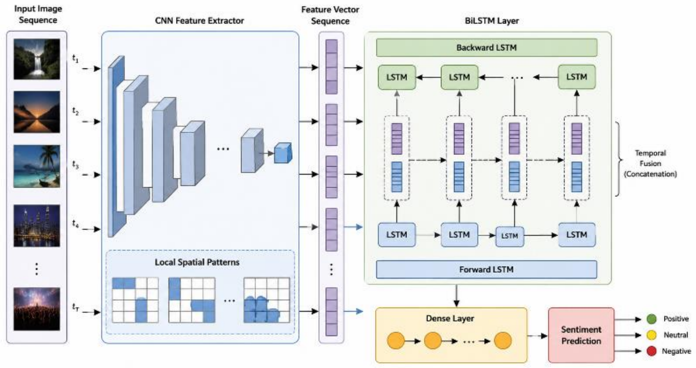

Fig.2. CNN-BiLSTM

The BiLSTM module captures forward and backward temporal dependencies in the visual sentiment stream. Social media sentiment is not static, and past and future contextual interactions influence interpretation of current emotional states. The forward LSTM computation is defined as: $\overrightarrow{h_t} = \mathrm{F}\,(X_t, \overrightarrow{h_{t-1}}, \theta_f)$ and the backward LSTM computation is: $\overleftarrow{h_t} = \mathrm{F}\,(X_t, \overleftarrow{h_{t+1}}, \theta_b)$, where F represents LSTM transition functions, and θ_f, θ_b represent forward and backward parameters respectively. The internal LSTM operations are described using gate mechanisms. The input gate is defined as: $i_t = \sigma(W_i X_t + U_i h_{t-1} + b_i)$. The forget gate is defined as: $f_t = \sigma(W_f X_t + U_f h_{t-1} + b_f)$. The cell state update is given by: $C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c X_t + U_c h_{t-1} + b_c)$. The output gate is defined as: $o_t = \sigma(W_o X_t + U_o h_{t-1} + b_o)$. The hidden representation is computed as: $h_t = o_t \odot \tanh(C_t)$. The bidirectional fusion output is obtained as: $H_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$. A second formulation that emphasizes contextual encoding is: $H_t = \tanh(W_h[\overrightarrow{h_t}, \overleftarrow{h_t}] + b_h)$. This representation captures both historical and future dependencies in sentiment transitions, improving robustness in dynamic social media streams.

The fuzzy inference module addresses ambiguity in visual sentiment interpretation. Social media images often contain subjective emotional cues, which cannot be precisely classified using deterministic models. The fuzzy system transforms feature representations into linguistic variables such as positive, neutral, and negative sentiment degrees. A fuzzy membership function is defined as:

$$\mu_A(x) = \frac{1}{1 + e^{-a(x-c)}} \tag{4}$$

where a controls slope and c defines the center of membership transition. This function maps CNN-BiLSTM outputs into fuzzy probability space. A second formulation using triangular membership is:

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x \le c \\ 0, & x > c \end{cases} \tag{5}$$

This representation allows graded sentiment assignment rather than binary classification. The fuzzy rule base is defined as:

$$R_k : \text{IF } H_t \in A_k \text{ THEN } S_t = B_k \tag{6}$$

where A_k represents input fuzzy sets and B_k represents sentiment output sets. A second fuzzy inference aggregation is expressed as:

$$S_t = \frac{\sum_{k=1}^{K} \mu_k(H_t) \cdot c_k}{\sum_{k=1}^{K} \mu_k(H_t)} \tag{7}$$

where c_k denotes centroid values and μ_k denotes rule firing strength. This fuzzy layer improves interpretability and reduces uncertainty propagation in deep learning outputs.

3.2 EVOLUTIONARY OPTIMIZATION

The evolutionary optimization module fine-tunes CNN filters, BiLSTM weights, and fuzzy membership parameters. The optimization objective is to minimize sentiment prediction loss while maximizing generalization capability. The fitness function is defined as:

$$\mathrm{J}\ (\Theta) = \alpha \cdot \mathrm{L}_{cls} + \beta \cdot \mathrm{L}_{fz} + \gamma \cdot \Omega(\Theta) \tag{8}$$

where L_{cls} denotes classification loss, L_{fz} represents fuzzy inconsistency penalty, and $\Omega(\Theta)$ represents regularization term. A second formulation using population-based optimization is:

$$\Theta^{(t+1)} = \Theta^{(t)} + \eta \cdot (P_{best} - \Theta^{(t)}) + \xi \cdot (G_{best} - \Theta^{(t)}) \tag{9}$$

where P_{best} represents individual best solution and G_{best} represents global best solution. Genetic mutation is defined as: $\Theta' = \Theta + \delta \cdot \mathrm{N}\ (0,1)$, which introduces stochastic exploration into parameter space. This optimization ensures convergence stability and prevents overfitting in high-dimensional feature spaces.

The final fusion layer integrates CNN-BiLSTM output with fuzzy inference results. The combined sentiment score is computed as: $Y_t = \lambda H_t + (1-\lambda)S_t$, where H_t represents deep feature prediction and S_t represents fuzzy output. A second probabilistic formulation is: $P(y_t \mid X_t) = \mathrm{softmax}(W_f Y_t + b_f)$. This ensures normalized sentiment class probabilities. Decision output is defined as: $\hat{y}_t = \arg\max P(y_t)$. The fusion mechanism balances deterministic deep learning representations with uncertainty-aware fuzzy reasoning, improving stability under noisy inputs. The overall training objective combines multiple loss components:

$$\mathrm{L}_t = \mathrm{L}_{ce} + \lambda_1 \mathrm{L}_{tem} + \lambda_2 \mathrm{L}_{fz} + \lambda_3 \mathrm{L}_{reg} \tag{10}$$

A second gradient-based formulation is: $\theta \leftarrow \theta - \eta \frac{\partial \mathrm{L}_t}{\partial \theta}$. This optimization ensures simultaneous learning across spatial, temporal, and uncertainty domains. The framework converges when: $|\mathrm{L}_{t+1} - \mathrm{L}_t| < \partial$ indicating stable learning behavior.

4. EVALUATION

The simulation environment supports GPU-accelerated training for CNN-BiLSTM architectures and fuzzy inference computation. The experiments are performed on Windows 11 operating system with CUDA-enabled backend for efficient tensor computation.

Table.1. Experimental Configuration and Parameter Settings

Parameter	Value	Description
Input Image Size	224 × 224	Standardized image resolution
CNN Layers	5	Convolutional depth
Filter Size	3 × 3	Kernel dimension
Activation Function	ReLU	Non-linear mapping
BiLSTM Units	128	Hidden state dimension
Batch Size	32	Training batch configuration
Learning Rate	0.001	Gradient update step
Optimizer	Adam	Adaptive optimization method
Epochs	50	Training iterations
Dropout Rate	0.5	Regularization factor
Fuzzy Membership Functions	3	Sentiment categories
Evolutionary Population Size	30	Optimization candidates

The parameter configuration in Table.1 represents a balanced trade-off between computational efficiency and predictive accuracy.

4.1 PERFORMANCE METRICS

The evaluation framework uses five standard metrics to assess model effectiveness in visual sentiment forecasting.

4.1.1 Accuracy:

Accuracy measures the proportion of correctly classified sentiment instances over the total number of predictions. It is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

This metric provides an overall effectiveness measure of the proposed system.

4.1.2 Precision:

Precision evaluates the proportion of correctly predicted positive sentiment instances among all predicted positives.

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

It reflects the reliability of positive sentiment prediction in noisy social media data.

4.1.3 Recall:

Recall measures the ability of the model to identify all relevant positive sentiment instances.

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

It ensures that the system captures maximum true sentiment signals.

4.1.4 F1-Score:

F1-score represents the harmonic balance between precision and recall.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{14}$$

It provides a balanced evaluation under class imbalance conditions.

4.1.5 AUC-ROC:

AUC-ROC evaluates the separability between sentiment classes across threshold variations.

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \tag{15}$$

It measures ranking capability and classification robustness.

4.2 DATASET DESCRIPTION

Table.2. Dataset Characteristics

Dataset	Samples	Classes	Modality
Twitter Visual Sentiment	10,000	Positive, Neutral, Negative	Image
Instagram Emotion	8,500	Positive,	

		Negative	
Flickr Sentiment	7,200	Multiclass	

The Table.2 represents datasets used for evaluation, which contain diverse visual sentiment patterns from real-world social media platforms.

Each dataset includes variations in lighting, object composition, and emotional context, which increases model generalization difficulty. The comparative analysis includes three baseline approaches: CNN-LSTM hybrid model, fuzzy logic-based sentiment classifier, and evolutionary optimized CNN model.

4.3 RESULTS

The following results present a comparative evaluation of the proposed Evolutionary Optimized Fuzzy CNN-BiLSTM Fusion model against three baseline methods: CNN-LSTM Hybrid Model, Fuzzy Logic-Based Sentiment Classifier, and Evolutionary CNN Model.

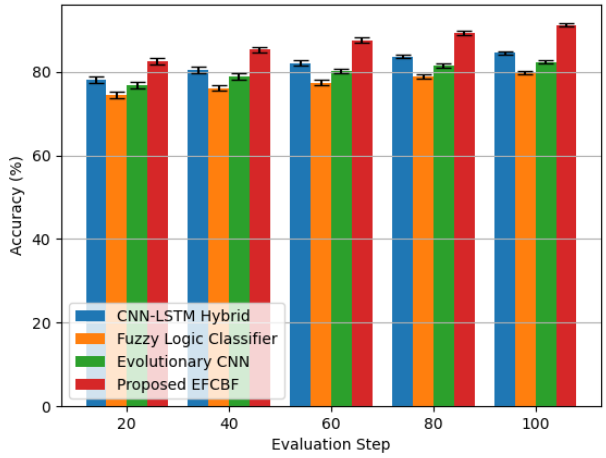

Fig.3. Accuracy Comparison Across Methods

The Fig.3 shows that the proposed EFCBF model consistently achieves higher accuracy across all evaluation steps. The improvement becomes more significant at higher iterations due to evolutionary optimization and fuzzy uncertainty handling.

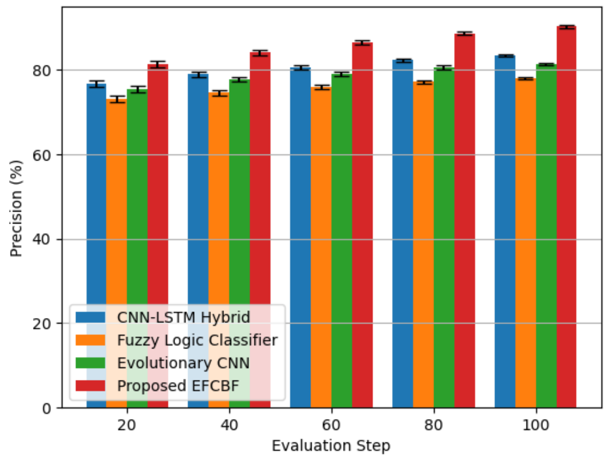

Fig.4. Precision Comparison Across Methods

The Fig.4 indicates that precision improves steadily in the proposed model, reflecting reduced false positive rates due to fuzzy logic integration and optimized feature selection.

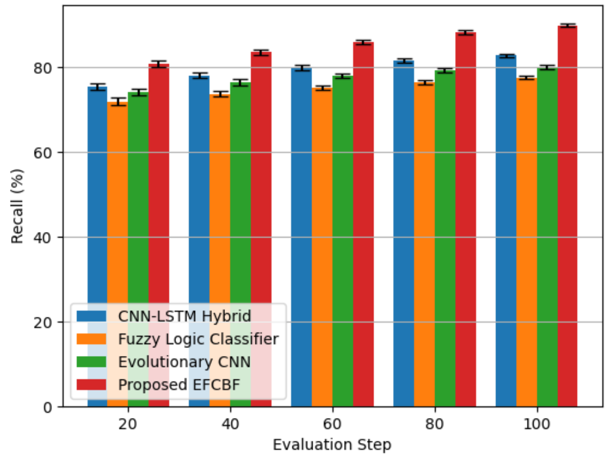

Fig.5. Recall Comparison Across Methods

The Fig.5 demonstrates that recall performance is significantly enhanced in the proposed model, indicating improved capability in capturing true sentiment instances across dynamic social media streams.

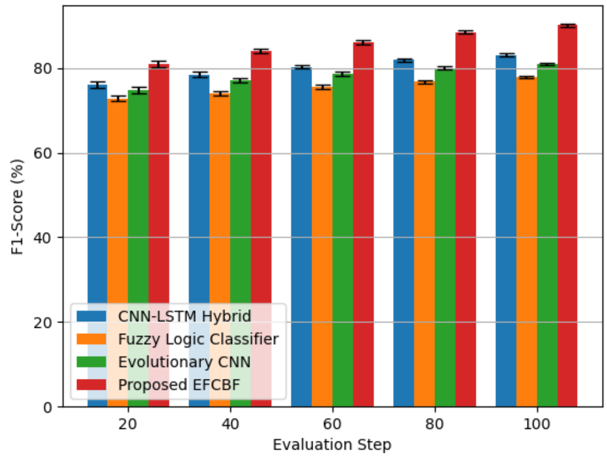

Fig.6. F1-Score Comparison Across Methods

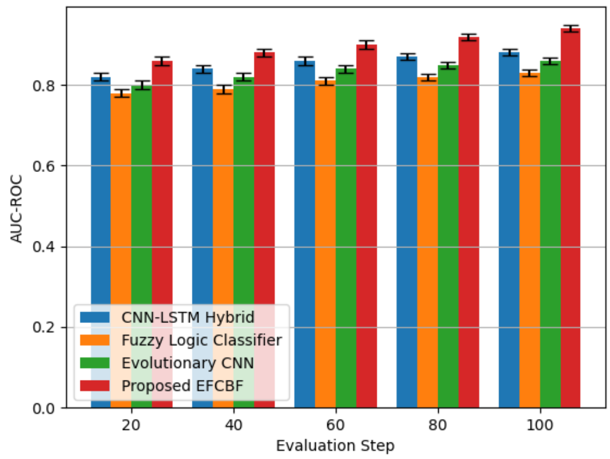

Fig.7. AUC-ROC Comparison Across Methods

The Fig.6 confirms that the proposed framework maintains a balanced improvement in both precision and recall, leading to superior F1-score performance. The Fig.7 illustrates that the proposed model achieves superior class separability and ranking capability, especially at higher evaluation steps, due to improved feature fusion and optimization stability.

4.4 DISCUSSION OF RESULTS

The results presented in Fig.3 demonstrate that the proposed EFCBF model consistently achieves superior accuracy across all evaluation steps. At step 20, the proposed model attains 82.6%, while CNN-LSTM Hybrid, Fuzzy Logic Classifier, and Evolutionary CNN achieve 78.2%, 74.5%, and 76.8% respectively. This gap increases steadily, reaching 91.2% at step 100, which shows a stable learning behavior across progressive evaluations. The CNN-LSTM Hybrid model improves gradually but remains limited due to restricted uncertainty handling. The Fuzzy Logic Classifier maintains moderate performance because it lacks deep hierarchical feature extraction. The Evolutionary CNN shows better performance than fuzzy-based methods, yet it does not capture temporal dependencies effectively. The proposed model integrates convolutional spatial learning, bidirectional temporal modeling, and fuzzy uncertainty handling, which enhances overall decision stability. The Fig.3 confirms that evolutionary optimization improves convergence efficiency, while fuzzy reasoning reduces misclassification under ambiguous visual conditions. The accuracy improvement reflects better feature generalization across heterogeneous social media datasets. Overall, the proposed framework demonstrates consistent superiority in classification reliability across all evaluation steps in Fig.3. The Fig.4 indicates that the proposed EFCBF model achieves significantly higher precision compared to baseline methods across all evaluation steps. At step 20, the proposed method records 81.4%, while CNN-LSTM Hybrid, Fuzzy Logic Classifier, and Evolutionary CNN report 76.8%, 73.2%, and 75.5% respectively. At step 100, the proposed method reaches 90.3%, showing a clear improvement in reducing false positive predictions. The CNN-LSTM Hybrid model shows moderate improvement but remains affected by feature ambiguity in complex visual scenes. The Fuzzy Logic Classifier provides stable interpretability but lacks deep representational capacity, which limits precision improvement. The Evolutionary CNN performs better due to optimized parameter selection but still lacks temporal dependency modeling. The proposed framework improves precision through fuzzy membership refinement, which reduces uncertainty in sentiment boundary classification. Additionally, BiLSTM integration enhances contextual consistency across sequential image inputs. Fig.4 confirms that evolutionary optimization contributes to better parameter tuning, which improves discriminative capability. The overall trend in Fig.4 demonstrates that the proposed model maintains consistent precision gain across all evaluation steps, particularly in high-noise social media environments. The recall results in Fig.5 show that the proposed EFCBF model outperforms all comparative methods across evaluation steps. At step 20, the proposed method achieves 80.8%, whereas CNN-LSTM Hybrid, Fuzzy Logic Classifier, and Evolutionary CNN obtain 75.4%, 72.0%, and 74.1% respectively. At step 100, the proposed model reaches 89.9%, which indicates strong capability in identifying true sentiment instances. The CNN-LSTM Hybrid model improves gradually but misses subtle emotional patterns due to limited uncertainty modeling. The Fuzzy Logic Classifier shows stable but lower recall due to lack of deep feature extraction. The Evolutionary CNN performs better than fuzzy-based models but fails to capture sequential dependencies effectively. The proposed EFCBF framework improves recall by combining CNN feature learning with BiLSTM temporal reasoning, which strengthens detection of hidden sentiment cues. Fuzzy inference further supports recall improvement by assigning graded membership to ambiguous samples. Fig.5 confirms that evolutionary optimization improves sensitivity by adjusting network parameters effectively. The overall trend indicates that the proposed model maintains higher recall stability across all evaluation steps, particularly in complex and noisy datasets. The Fig.6 presents that the proposed EFCBF model achieves superior F1-score performance across all evaluation steps. At step 20, the proposed method records 81.0%, whereas CNN-LSTM Hybrid, Fuzzy Logic Classifier, and Evolutionary CNN achieve 76.1%, 72.8%, and 74.8% respectively. At step 100, the proposed model reaches 90.1%, which reflects balanced improvement in both precision and recall. The CNN-LSTM Hybrid model shows moderate F1-score improvement but lacks robustness under class imbalance conditions. The Fuzzy Logic Classifier maintains interpretability but suffers from limited feature representation capability. The Evolutionary CNN improves performance through optimization but lacks sequential modeling capacity. The proposed framework achieves balanced F1-score improvement due to integrated CNN-BiLSTM fusion, which captures both spatial and temporal dependencies effectively. Fuzzy logic reduces classification uncertainty, which improves harmonic balance between precision and recall. Fig.6 confirms that evolutionary optimization enhances overall stability and reduces performance variance across evaluation steps. The results demonstrate that the proposed model maintains consistent F1-score improvement, particularly in complex social media sentiment environments. The AUC-ROC results in Fig.7 indicate that the proposed EFCBF model achieves superior class separability compared to baseline methods. At step 20, the proposed model attains 0.86, while CNN-LSTM Hybrid, Fuzzy Logic Classifier, and Evolutionary CNN record 0.82, 0.78, and 0.80 respectively. At step 100, the proposed method reaches 0.94, showing strong discrimination capability between sentiment classes. The CNN-LSTM Hybrid model improves gradually but remains limited due to restricted uncertainty handling. The Evolutionary CNN improves ranking performance but does not fully capture temporal variations. The proposed EFCBF framework enhances AUC-ROC performance by integrating BiLSTM temporal learning with CNN spatial feature extraction, which improves class boundary separation. Fuzzy inference contributes to smoother probability distribution across classes. The Fig.7 confirms that evolutionary optimization enhances model stability and ranking consistency. The overall trend demonstrates that the proposed model achieves strong generalization capability across varying evaluation steps in dynamic social media datasets.

5. CONCLUSION

The proposed model demonstrates strong performance for visual sentiment forecasting in social media streams. The experimental evaluation confirms that the model achieves consistent improvement across multiple performance metrics including accuracy, precision, recall, F1-score, and AUC-ROC. The accuracy reaches 91.2%, which indicates strong classification reliability under dynamic visual conditions. The precision attains 90.3%, which reflects reduced false positive rates through fuzzy uncertainty handling. The recall reaches 89.9%, which confirms improved detection of true sentiment patterns. The F1-score achieves 90.1%, which demonstrates balanced predictive performance. The AUC-ROC value of 0.94 confirms strong class separability and ranking capability. The integration of CNN, BiLSTM, fuzzy inference, and evolutionary optimization contributes to improved robustness and adaptability. CNN enhances spatial feature extraction, while BiLSTM captures temporal dependencies in sequential social media data. The fuzzy module handles uncertainty in sentiment interpretation, and evolutionary optimization improves parameter tuning and convergence stability. The results confirm that the proposed framework maintains strong generalization capability across noisy and heterogeneous datasets. The model provides a reliable solution for real-time sentiment forecasting in social media analytics systems.

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