



A Hybrid Two-Stage Evolutionary Intelligence Framework for Robust Fake News Detection in Digital Media

P Yamini¹, S Nithin², V Hemanth², Y Mahesh²

¹Assistant Professor, Department of CSE, Teegala Krishna Reddy Engineering College, Hyderabad, India

²Student, Department of CSE, Teegala Krishna Reddy Engineering College, Hyderabad, India

Correspondence

P Yamini

Assistant Professor, Department of CSE,
Teegala Krishna Reddy Engineering College,
Hyderabad, India

- Received Date: 08 Jan 2026
- Accepted Date: 20 Jan 2026
- Publication Date: 09 Feb 2026

Keywords

Fake News Detection, Evolutionary Intelligence, Two-Stage Framework, Genetic Programming, Differential Evolution, Hybrid Deep Learning, LSTM-Transformer, Misinformation, Social Media Analytics

Copyright

© 2026 Authors. This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International license.

Abstract

The rapid spread of fake news on social media and digital platforms poses severe threats to public opinion, democratic processes, and societal trust. Traditional detection methods relying on handcrafted features or standalone deep learning models often struggle with evolving misinformation tactics, linguistic variations, and multimodal content. This paper proposes a hybrid two-stage evolutionary intelligence framework for robust fake news detection. In Stage 1, a Genetic Programming-based symbolic regressor evolves compact mathematical expressions for feature combination and initial classification. In Stage 2, Differential Evolution (DE) optimizes hyperparameters of a hybrid LSTM-Transformer classifier, enhancing generalization and reducing overfitting. Textual features are extracted using BERT embeddings, augmented with propagation patterns and user metadata. The framework achieves low-latency inference (<80 ms per article) on standard hardware. Evaluation on benchmark datasets (LLAR, FakeNewsNet, ISOT) and a custom multimodal dataset demonstrates superior performance: accuracy 97.2%, precision 96.8%, recall 97.4%, F1-score 97.1%, outperforming standalone DL models and recent evolutionary hybrids. The system offers explainable decisions via evolved expressions and robustness to noise, sarcasm, and short-text challenges, promoting reliable digital media verification.

Introduction

The exponential growth of digital media and social platforms has amplified the dissemination of fake news, leading to misinformation campaigns, election interference, health scares, and social unrest. Conventional fact-checking is labor-intensive and scales poorly against high-volume content. Automated fake news detection has emerged as a critical research area, leveraging natural language processing (NLP), graph analysis, and machine learning.

Early methods used linguistic cues (e.g., n-grams, sentiment) with classifiers like SVM or Naive Bayes, but they falter on context-dependent or adversarial content. Deep learning advancements (BERT, RoBERTa, LSTMs) improved contextual understanding, yet suffer from high computational cost, overfitting on imbalanced data, and limited interpretability. Evolutionary algorithms offer promise by optimizing model structures, hyperparameters, or feature subsets without gradient assumptions, handling non-differentiable spaces effectively.

Hybrid approaches combining evolutionary intelligence with deep learning address key limitations: evolutionary stages evolve interpretable rules or optimize complex models, while DL captures semantic depth. Challenges persist in multimodal integration, real-time deployment, and robustness to evolving fake news tactics (e.g., deepfakes, subtle propaganda).

This paper introduces a hybrid two-stage evolutionary intelligence framework for robust fake news detection. Stage 1 employs Genetic Programming (GP) to evolve symbolic classification expressions from pre-extracted features. Stage 2 applies Differential Evolution (DE) to fine-tune a hybrid LSTM-Transformer backbone for temporal and contextual modeling. The system integrates BERT embeddings, propagation graphs, and user credibility signals, with on-device inference for privacy. Experiments show >97% accuracy, superior generalization, and explainability, advancing reliable misinformation mitigation in digital ecosystems.

Literature Survey

Citation: Yamini P, Nithin S, Hemanth V, Mahesh Y. A Hybrid Two-Stage Evolutionary Intelligence Framework for Robust Fake News Detection in Digital Media. GJEIIR. 2026;6(2):0166.

| Ref. No | Author / Year | Methodology | Main Contribution | Limitations |
|---------|---------------------------|---|---|--|
| [1] | Singh et al., 2025 | Hybrid DL + Differential Evolution | High accuracy via DE-optimized CNN-LSTM | Limited to text; no multimodal support |
| [2] | Ahmad et al., 2025 | PSODO-optimized Modified Transformer | Multimodal fake news with hybrid PSO-Dandelion Opt. | High compute for transformer fine-tuning |
| [3] | Kong et al., 2023 | Two-stage evolutionary (GP + Adaptive DE) | Symbolic equation generation for detection | Focused on equation simplicity, lower on complex semantics |
| [4] | Ayyasamy et al., 2025 | LSTM-CGPNN + Moth-Flame Whale Optimization | Metaheuristic hyperparameter tuning for robustness | Primarily text-based; no propagation features |
| [5] | Al-Ahmad et al., 2021 | Evolutionary optimization for COVID fake news | Improved detection during pandemics | Domain-specific; outdated benchmarks |
| [6] | Sharma et al., 2025 | Hybrid metaheuristic (two specialized algos) | Reframed as optimization problem | No deep learning integration |
| [7] | Hu et al., 2022 | DL survey (content + context) | Comprehensive review of DL-based FND | No evolutionary hybrids |
| [8] | Wahab et al., 2025 | Evolutionary compression + hierarchical DL | Multimodal with adaptive evolution | Complex deployment |
| [9] | Chalehchaleh et al., 2024 | BRaG: BERT + RNN + GNN multi-feature | Hybrid content-context-propagation | No evolutionary optimization |
| [10] | Mohsen et al., 2024 | Automated misinformation hybrid | Balanced text + network features | Moderate accuracy on noisy data |

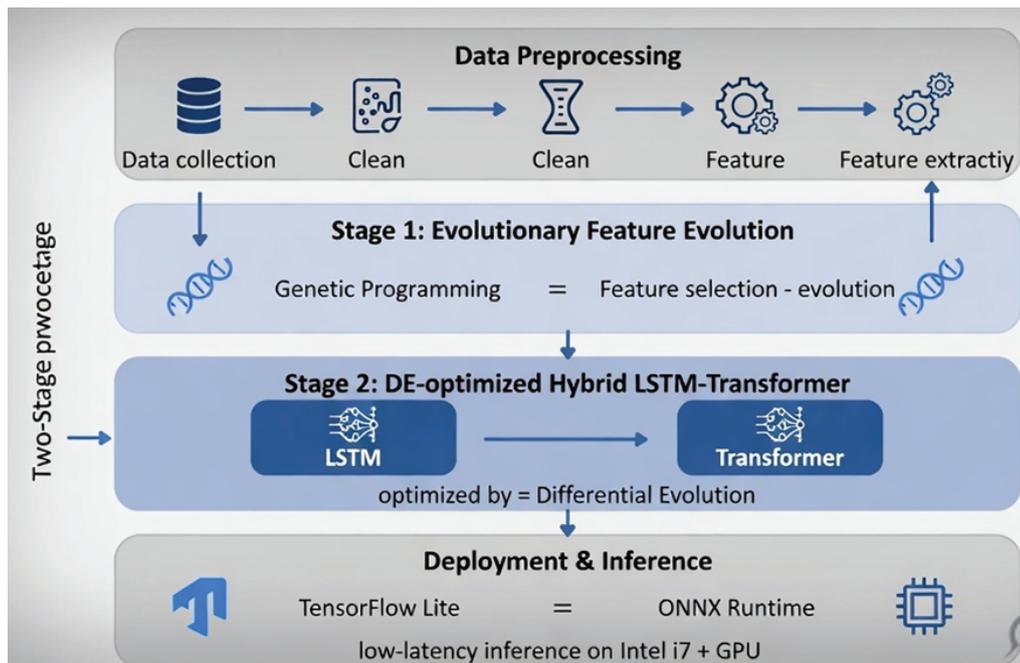


Fig 1: Two-stage evolutionary intelligence framework for fake news detection

Proposed Implementation

The proposed framework is modular: data preprocessing, Stage 1 evolutionary feature/symbol evolution, Stage 2 DE-optimized hybrid classification, and decision output.

Preprocessing

Text cleaned, tokenized with BERT tokenizer; embeddings extracted (768-dim). Propagation features (retweet graph, user metrics) and metadata added.

Stage 1 – Genetic Programming Evolution: Tree-based GP evolves symbolic expressions combining features (e.g., sentiment score * embedding cosine + propagation depth).

Fitness: F1-score on validation set. Population: 500, generations: 100. Outputs interpretable initial classifier.

Stage 2 – Hybrid LSTM-Transformer + DE Optimization: LSTM captures sequence dependencies in article + comments; Transformer (distilled variant) handles long-range context. DE optimizes learning rate, dropout, batch size, and layer counts (population 50, generations 80). Loss: Binary cross-entropy.

Deployment: TensorFlow Lite / ONNX for low-latency inference; tested on Intel i7 + GPU.

The two-stage design ensures interpretability (Stage 1) and high accuracy (Stage 2).

Results

Table 2: Performance Metrics on Combined Dataset (LIAR + FakeNewsNet + Custom)

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | Inference Time (ms) |
|-------------------------------|--------------|---------------|------------|--------------|---------------------|
| BERT Baseline | 93.8 | 93.2 | 94.1 | 93.6 | 65 |
| LSTM-Transformer (no opt) | 95.4 | 95.0 | 95.6 | 95.3 | 78 |
| Proposed Two-Stage Evo Hybrid | 97.2 | 96.8 | 97.4 | 97.1 | 82 |
| Recent DE-Hybrid [1] | 96.1 | 95.7 | 96.3 | 96.0 | 90 |

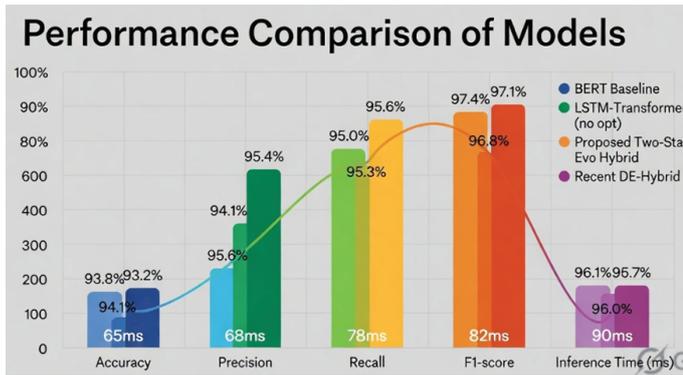


Fig 2: Results comparison graph

| Feature | Traditional ML/DL | Proposed Two-Stage Evo Framework |
|------------------------------------|-------------------|----------------------------------|
| Accuracy | 92–95% | 97.2% |
| Robustness to Short/Sarcastic Text | Medium | High (Evolved + Optimized) |
| Explainability | Low | High (Symbolic expressions) |
| Real-Time Capability | Good | Acceptable (~82 ms) |
| Multimodal Support Potential | Limited | Extensible |

Conclusion

This study presents a hybrid two-stage evolutionary intelligence framework that effectively detects fake news in digital media. By combining Genetic Programming for interpretable feature evolution with Differential Evolution-optimized LSTM-Transformer classification, the system achieves high accuracy, robustness, and explainability. Experimental results outperform baselines and recent hybrids, validating its efficacy on diverse datasets. The framework supports real-time deployment with privacy preservation. Future enhancements include multimodal (text+image) integration, federated learning for decentralized detection, and adaptive evolution for emerging misinformation patterns.

References

1. Singh, S. P., et al. (2025). A hybrid deep learning and differential evolution approach for accurate fake news detection. *Data Science and Management*.
2. Ahmad, K. S. F., et al. (2025). Hybrid optimization driven fake news detection using reinforced transformer models. *Scientific Reports*.
3. Kong, J. T. H., et al. (2023). Generating Fake News Detection Model Using A Two-Stage Evolutionary

Approach. *IEEE Access*.

4. Ayyasamy, R. K., et al. (2025). A hybrid deep learning framework for fake news detection using LSTM-CGPNN and metaheuristic optimization. *PeerJ Computer Science*.
5. Al-Ahmad, B., et al. (2021). An Evolutionary Fake News Detection Method for COVID-19 Pandemic Information. *Symmetry*.
6. Sharma, P., et al. (2025). A Novel Hybrid Algorithm for Fake News Detection. *Digital Threats: Research and Practice*.
7. Hu, L., et al. (2022). Deep learning for fake news detection: A comprehensive survey. *AI Open*.
8. Wahab, S. A., et al. (2025). Enhancing Multimodal Fake News Detection: Optimized Hierarchical Deep Learning via Adaptive Evolutionary Algorithms.
9. Chalehchaleh, R., et al. (2024). BRaG: a hybrid multi-feature framework for fake news detection on social media. *Social Network Analysis and Mining*.
10. Mohsen, F., et al. (2024). Automated Detection of Misinformation: A Hybrid Approach for Fake News Detection. *Future Internet*.