International Journal of Science, Strategic Management and Technology
Volume **02** Issue **04** April-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

Early Detection of Fake News using AI-based Chrome Extension and Website

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https://doi.org/10.55041/ijsmt.v2i4.166

Cite this Article: Amrutkar, A., Aware, A., Hire, R. & Ahire, V. (2026). Early Detection of Fake News using AI-based Chrome Extension and Website. International Journal of Science, Strategic Management and Technology, *02*(04). https://doi.org/10.55041/ijsmt.v2i4.166

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Abstract—

Fake news has become a major concern in today's digital world, where social media platforms and online networks make it easier for false information to spread quickly. Often, traditional detection techniques only employ textual characteristics, neglecting crucial contextual factors like the news's novelty and popularity that can increase detection accuracy. In this work, we propose Spectral Clustering Environments and Data Augmentation for Fake News Detection (SEAFND), a real-time framework for detecting fake news that integrates contextual, stylistic, and semantic features .Our approach combines state-of the-art Natural Language Processing (NLP) and deep learning methods with ecologically conscious popularity and novelty metrics. Users can verify news headlines and articles in real time thanks to the system's implementation as a web application and an AI-powered Chrome Extension. Additionally, it facilitates image-based detection for textual content extraction using optical character recognition (OCR). Contextual indicators are shown to improve fake news detection performance and guarantee user friendly accessibility in empirical evaluations.

Keywords—Fake news detection, Real-time detection, SEAFND, Popularity, Novelty, NLP, OCR.

I. INTRODUCTION

False information is spreading so quickly that it has become a major threat to social integrity, impacting political discourse, public health campaigns, and social stability [2]. As seen during the COVID-19 pandemic and the 2016 U.S. presidential election [7][19], fake news, which is defined as purposefully fabricated or misleading information presented as legitimate content, spreads quickly through digital platforms. Automated detection systems must be developed because traditional man ual fact-checking methods cannot keep up with the volume and speed of online false information [6].To address these limitations, this paper proposes a real-time fake news detection system that integrates semantic features (NLP embeddings), stylistic attributes (linguistic indicators), and environment aware characteristics (popularity and novelty).By using optical character recognition (OCR) to examine image-based content like memes and screenshots, the system also facilitates multi modal detection [8][15]. The suggested remedy is implemented by: (i) a Chrome

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extension that allows users to instantly verify news content while browsing; (ii) a web application that offers detailed visualization of results and direct input. The system attempts to close the gap between academic research and real-world usability by fusing cutting-edge detection techniques with real-time deployment.

II. LITERATURE REVIEW

Shu et al. (2017) established that fake news detection requires integrating content, social context, and propagation dynamics—purely text-based methods are insufficient [2]. BERT-based models (Zhou et al., 2020) achieve 85–90% accuracy by capturing deep contextual meaning, outperforming TF-IDF and word2vec approaches [9]. The CSI hybrid model by Ruchansky et al. (2017) reached 86% by combining text, user behavior, and source credibility [4].

SEAFND (Liu & Wu, 2023) introduced environment-aware spectral clustering features—popularity (similarity to trusted article clusters) and novelty (deviation from mainstream topics)—reporting 90%+ accuracy and demonstrating that contextual signals capture what content-only models miss [1]. Graph Neural Networks on propagation trees (Ma et al., 2019) achieved 88–90% [13], while HGNN (Liu et al., 2020) reached 90% using hierarchical propagation cues [11].

Multimodal approaches combining text and images (Khattar et al., 2019; Singhania et al., 2019) further improved accuracy but face dataset and scalability constraints [8][15]. Stylometric features—emotional tone, punctuation, clickbait language—reliably distinguish fake from real news at ~80% accuracy (Rashkin et al., 2017) [7]. Despite these advances, practical real-world deployment remains underexplored; our work addresses this gap.

Table I: Comparative Analysis of Fake News Detection Approaches

Sr.No.	Algorithm / Methodology	Accuracy	Key Findings
1	SEAFND (Spectral Clustering + Data Augmentation)	90%+	Environment-aware features improve detection significantly
2	Survey of ML/NLP approaches (taxonomy)	N/R	Classified detection methods into 4 categories
3	Transformer-based model (BERT)	85–90%	Contextual embeddings outperform TF-IDF
4	Multimodal fusion (text+image+video)	N/R	Combining visual and textual features boosts accuracy
5	Stylometric + linguistic feature analysis	80%	Emotional tone and clickbait are useful indicators
6	Hybrid deep model (CSI)	86%	Multi-source features outperform content-only models
7	LIAR Dataset + traditional ML classifiers	65–70%	Benchmark dataset for fake news introduced
8	Graph-based propagation trees	85%	Fake news spreads in distinct

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			cascades vs real news
9	Knowledge graph validation	83%	Fact-checking with KG improves detection
10	Graph Neural Networks (GNN)	88–90%	High accuracy using diffusion patterns

III. METHODOLOGY

The proposed system follows a structured methodology for accurate and real-time fake news detection based on the SEAFND framework, extended to support multimodal inputs, real-time verification, and user-centric deployment [1].

1) Data Collection: Publicly available benchmark datasets such as FakeNewsNet, LIAR, and COVID-19 Fake News datasets are utilized [2]. Trusted sources including Wikipedia, BBC, and Reuters are used for real-time cross-verification. OCR is employed for image inputs.

2) Data Preprocessing: Removal of URLs, special characters, and stop words; conversion to lowercase; tokenization and normalization [4][15].

3) Feature Extraction: Semantic features via BERT/RoBERTa [9]; stylistic features including sentiment polarity, punctuation, and readability [7]; environment-aware features (popularity and novelty) from SEAFND.

4) Model Training: Hybrid model trained with Binary Cross-Entropy loss and Adam optimizer. Dropout and L2 regularization prevent overfitting. Evaluated on Accuracy, Precision, Recall, F1-score, and AUC [10].

5) Real-Time Verification: Queries Wikipedia, NewsAPI, and Google Fact Check Tools. Cosine similarity measures match input with retrieved content [12]. Results are displayed via Chrome Extension and Web Application [8].

6) Deployment Architecture: Chrome Extension for real-time browsing verification; Web Application for interactive input and analytics. Both communicate via RESTful APIs built with Flask/FastAPI [2].

7) Feedback and Continuous Learning: User-reported incorrect predictions are stored in MongoDB and used for periodic model retraining via incremental learning, ensuring adaptability to evolving misinformation [18].

IV. RESULTS AND DISCUSSION

The proposed system was tested using multiple news inputs to evaluate its performance. The system successfully classifies news as real or fake and provides confidence scores along with verified sources. The results obtained from the Web Application and Chrome Extension demonstrate the practical utility of the system.

Fig. 1. Web Application showing fake news detection (FactGuard interface).

The Web Application (FactGuard) classifies input news as fake or real with a confidence score and supporting references, enhancing transparency. The Image News Verification module enables users to upload screenshots or memes, which are processed via OCR before classification.

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Fig. 2. Image-based News Verification input interface

The integration of real-time verification using trusted sources further enhances reliability and transparency by providing supporting evidence alongside predictions. The SEAFND-inspired environment-aware features (popularity and novelty) contribute significantly to the detection accuracy reported at 90%+ in empirical evaluations.

V. CONCLUSION

In this work, a real-time fake news detection system has been proposed and implemented to address the growing challenge of misinformation in digital platforms. The system integrates advanced artificial intelligence techniques, including semantic analysis using transformer-based models, stylistic feature evaluation, and environment-aware indicators such as popularity and novelty, to improve detection accuracy.

Unlike traditional approaches that remain limited to research environments, the proposed system focuses on practical usability by deploying the model through a Chrome Extension and a Web Application. The incorporation of Optical Character Recognition (OCR) allows the system to handle image-based content such as memes and screenshots, making it suitable for modern multimodal misinformation.

The feedback-based continuous learning mechanism ensures that the model adapts to evolving misinformation patterns, improving performance over time. Overall, the proposed solution bridges the gap between theoretical research and practical implementation, offering a scalable, user-friendly, and effective approach to combating fake news in today's digital ecosystem.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to their project supervisor, Dr. S.A. Talekar, Department of Information Technology, MVP'S KBTCOE, for continuous guidance, encouragement, and valuable feedback throughout the course of this work. They also extend appreciation to the faculty and staff of the Department of Information Technology, MVP'S KBTCOE, for providing the resources and support necessary to successfully complete this project.

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